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Performance Based Analysis of Classification Techniques in Breast Cancer Screening – A Review

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***Abstract*: According to the survey of WHO, in 2020 there are 2.3 million women found with breast cancer and 685,000 deaths in world wide. 81% women get affected with cancer over the age of 50 at the time of detection. Breast cancer is the world's number 2 cancer and number 1 cancer in India and 66% survival rate in India is very low if compare to 90% in U.S and 90.2% in Australia. However, treatment for this cancer has possibility of 90% or more. So that, it needs to detect the cancer at very early stage to overcome the death rate. In healthcare sector, there are many ways for screening breast cancer like: mammography, sonography, ultrasound and MRI for detection of benign and malignant tumors before symptoms appear. There are some other ongoing experiments exist i.e., PET (positron emission tomography) scans, thermography, ductogram (ducto lavage, ductoscopy) etc. CAD system which are used for classification breast cancer abnormalities, assisting doctor as a second opinion. Now a days DL-CADs (Deep learning CAD) in use, which are better than traditional CADs for complex data analysis. This paper discussed the complete survey of deep learning techniques and data sets which are in use for breast cancer classification. And resulting with challenges/limitation or future work in this area of study.**

***Keywords*: Breast Cancer, Mammography, Computer Aided Detection (CAD), Sonography, Ultrasound, MRI, X-ray.**

1. Introduction

Cancer is a major cause of changes in the body's cells. Breast cancer develops from breast tissues, it usually starts when the breast tissues get abnormal. Thus, screening is very important step for detecting cancer in early stage. Cause of this cancer is mutation of genes like BRCA1, BRCA2, TP-53 etc. [1], [2]. It is most common in women but it can be in men too.

The main reason of low survival is lack of awareness about early symptoms & screening techniques, low treatment, non-availability of centres, lack of physician recommendation etc. Mammography began in 1913, from 1947 to 1970 is the second wave and since 1970 is 3rd wave that increases the value of mammography for detecting very early stage of breast cancer. The basic term mammogram is used which is a low dose X-ray of breast. An early stage of cancer can be detect with regular basis mammogram which provide a best accuracy rate of 85%. For mammography Standard bilateral craniocaudal(CC-Top view of breast) and mediolateral oblique(MLO- Side view of breast) imaging used for showing abnormality of breasts. At the early stage, if the rate of early detection of cancer is high then it will be very beneficial to many people in the world. For that we have to analyze all the cancer detection techniques used for screening. Mammography is the oldest and most common used technique to detect the cancer at early stage and sometimes prefer to use with addition of ultrasound for early detection. However, sensitivity of small tumor even in dense breast is high with MRI, ultrasound and CT-Scan. And CT-Scan cannot used on regular basis screening because it may increase the chance of cancer.

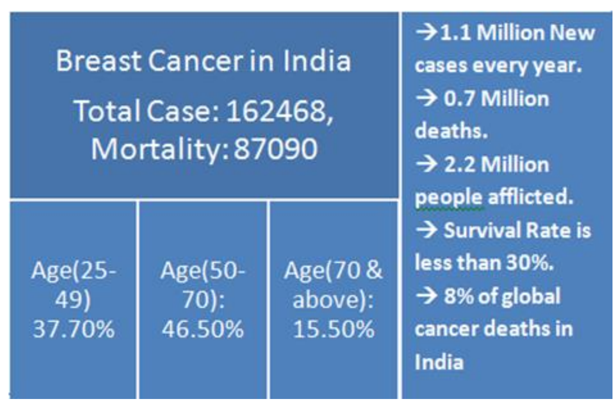

Fig. 1. According to NICPR and NBCF breast cancer in India

Country	New	Died	Ratio= new/died	Case rate
US	234,087	41,904	5.59	In every 6 new cases, 1 death
China	367,900	97,972	3.75	In every 4 new cases, 1 death
India	162,468	87,090	1.87	In every 2 new cases, 1 death

Fig. 2. India vs. China vs U.S breast cancer rate

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Table 1
Performance analysis of existing breast cancer screening methods

Method	Accuracy	Specificity	Sensitivity	Limitation
Film Mammography [1]	85%	88.9%	86.9%	Not sufficient for all types of breasts
Digital Mammography [3]	68%	48%	83%	Images are not fine as film mammograms have.
Ultrasound [3]	84%	86%	81%	It cannot detect small tumors.
MRI [1]	86.9%	95.5%	AUC=0.948%	It cannot differentiate cancerous abnormalities.
Tomosynthesis [3]	84%	86%	81%	It's not sufficient for all age groups.
CEM (Contrast Enhanced Mammography) [3]	89%	93.7%	89%	It may become risk of allergy because of contrast material.

Whereas X-rays can also be sometimes found the cause of cancer and MRI has the drawback of low sensitivity, specificity, complex, and expensive technique and [1] if patient have pacemaker or any mental implant then MRI not suitable. Various [3] screening tests are available for breast cancer detection where breast examination is part of this. Although, high sensitivity, specificity, accuracy, ease of implementation, and affordability are the basic requirements for breast cancer screening methods. In most of the cases, breast cancer rate often found high in age of 55-65 groups. [4] One of the major problems with breast cancer treatment is cancer not timely detected because of less availability of breast cancer detection techniques which provide us best accuracy. Till now lots of discoveries have done on breast cancer, but there's still so much else to learn about how it forms and how to treats it effectively.

A. *Breast Cancer Abnormalities*

Most of the cancer found after symptoms appear, but many women can get cancer without any symptom appear. Therefore, it is requirement of regular breast screening and early cancer detection techniques. The lymph system(network) which is a connection between lymph nodes, it helps for travelling the fluid from breast to other organs in body. If cancer cells enter in this lymph, it may spread cancer throughout the body.

Abnormalities can be of different size and different shapes in breast tissues as shown in figure,

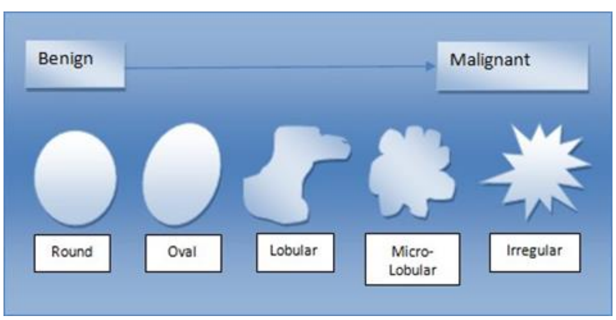

Fig. 3. Types of abnormalities or masses

[5] BI-RADS is a classification of breast cancer as- sessment into seven classes (0 through 6); 0th-incomplete; 1st-negative/no masses; 2nd-non cancerous; 3rd-benign; 4th-suspicious; 5th-highly suggestive malignancy; 6th-malignancy. And mammography breast measurement can be divided into four classes with respect to breast tissues as following- A) mostly fatty, B) scattered fibro-glandular, C) heterogeneously dense, and D) extremely dense.

When cells become out of control, it is the sign of abnormality in body. Mostly breast cancer starts from ducts (vessels which carry milk to nipple) has chances of 85-90% that called ductal carcinoma.

Another major factor is of cancer start from glands (which make breast milk) has chances 10-15% that called lobular carcinoma. And some other cancer which start from other tissues are called lymphomas or sacromas.

B. *Experimental Techniques*

1) *Positron Emission Tomography (PET)*

[3] It takes the concept that abnormal tissues have large amount of metabolise compare to normal tissues and they also require higher food than normal. Whenever radioactive layer passes through the vein of patient then it divide abnormal cells quickly from normal cells after detection and provide us an image.

2) *Ductal Lavage and Ductoscopy*

[3] 85% of breast cancer start from milk ducts. Indication is bloody nipple discharge, yellow nipple discharge or prior history of breast cancer. Useful to identify very early stage of breast cancer which mammography cannot do. But it has low sensitivity and high specificity.

- In ductal lavage, catheter placed into duct and then removed. Subsequent cells will wash out and examine with microscope.
- In ductoscopy, catheter placed into duct with a light via nipple. Then lavage ducts injected with colored dye which helpful for giving shape of duct and abnormality shows with X-ray.

3) *Electrical Impedance Spectral Imaging (EIS)*

[3] This method can detect cell changes in real time. In this electrical current pass-through tissue layers of breast. It based on the concept such that the electric current passes in different ways from normal and abnormal tissues.

4) *Microwave Imaging Spectroscopy (MIS)*

[3] Mi- crowave signal is used to detect cancer in breast and it achieved high precision. After passing microwave different tissues appear with different absorption and scattering rates.

5) *Near Infrared (NIR) Spectral Imaging*

[3] This method basically based on reaction of electromagnetic radiation which are sensitive to blood and used for defining image of breast's hemoglobin. It useful to detect early stage of cancer.

2. Dataset Used

1) *INbreast Database*

Origin of this database at Centro Hospitalar de S. Joao (CHSJ), Breast center. It basically the collection between April 2008 and July 2010 of FFDM (full field digital mammograms) format that contains 115 cases with 410 images. from 115 cases, 90 cases are from patient of both breasts affected and 25 cases from patient with two images per case. Images are in two types of view: the craniocaudal (CC- Top view of breast) and the mediolateral oblique (MLO- Side view of breast). And the density of breast also classified in 4 types: 1- Fatty, 2- Scattered fibro glandular densities, 3- Heterogeneously dense, and 4- Extremely dense.

2) DDSM Dataset

DDSM (Digital Database for Screening Mammography) is a collection of 2,620 scanned film mammography which has normal, benign, malignant cases and total of 10480 mammograms. The primary origin of this database is from the Breast Cancer Research Program of the U.S. Army Medical Research and Materiel Command.

3) OMI-DB Database

Optimam Mammography Imaging Database (OMI-DB) is a centralized database of mam- mogram images wchich is a collection of clinical data from multiple NHS screening sites. It is a collection of 2,623 cases or 2D 34,104 images.

4) MIAS Dataset

An organisation MIAS (Mammo- graphic Image Analysis Society) in UK generated this database which contains total of 322 digitised films which contain normal-208 films, benign-63 films and abnormal(malignant)- 51 films of 161 patients on 2.3GB 8mm (ExaByte) tape with resolution of 50 microns in PGM format and related to truth data. Size of all images are 1024 x 1024 and density range from 0-3.2.

5) CBIS-DDSM

It stands for the Curated Breast Imaging Subset of DDSM(CBIS-DDSM). CBSI-DDSM is a DDSM's standardized and upgraded version. It contains total of 10,239 images of 6671 subjects on 163.6 GB and also including ROI segmentation and bounding boxes and pathological diagnosis for training data.

6) IRMA Dataset

IRMA (Image Retrieval in Medical Applications) is a co-operative project of the Dept. of Medical Informative, the Dept. of Diagnostic Radiology, the Chair of Computer Science VI and Division of Medical Image Processing at the Aachen University of Technology (RWTH Aachen).

7) BCDR Database

The main two objective of BREAST CANCER DIGITAL REPOSITORY(BCDR) database is to explore CAD's & diagnosis methods and to train medical stu- dents. It contains 1734 cases of mammography and ultrasound images and subdivided into two parts:

- Film Mammography-based Repository (BCDR-FM): It has total of 1010 cases, including 1125studies, 3703 MLO & CC mammograms and other 1517 segmentation's collected.
- Full Field Digital Mammography-based Repository (BCDR-DM): It has total of 724 cases, including 1042 studies, 3612 MLO & CC mammograms and other 818 segmentation's collected.

8) WBCD dataset

WBCD (Wisconsin Breast Cancer Dataset) is a classification database from machine learning repository called UCI. There are two classes defined as benign and malignant. Fine needle aspirate (FNA) of breast mass computed from digitized images.

9) RCDT

Radon Cumulative Distribution Transform (RCDT) are the processed images, usually used for detecting mammographically-occult (MO) cancer cases.

3. Deep Learning Techniques

A. AlexNet

In deep learning an achievement result in 2012 was AlexNet which is a total of 8-layer architecture. Where 5 layers are convolution layers & 3 layers are fully connected layers. And it used the filter sizes of 11x11, 5x5, 3x3 with approximately 62 millions parameters. It's top 1 accuracy is 57% and top 5 is 80.3%.

B. VGG 16

It is a 19 layers model that uses only 3x3 filter and more convolution layers. Structure of over all VGG made with total 5 blocks where, first two blocks contain 2 convolution and 1 max pooling layer. And remaining three blocks contain 3 convolution and 1 max pooling layer. After 5 blocks 3 fully connected layers added, first 2 layers have 4096 neurons and remaining have 1000 neurons. It's top 1 accuracy is 71.3% and top 5 is 90.1%.

C. DenseNet

Two layered neural network classifier (pre-trained CNN model namely DenseNet Model-DenseNet121, DenseNet169, DenseNet201) is an advanced CNN feed forward model which pretrained on ImageNet database. Some advantages of this model are: promoting facility of reuse of feature, reduction of the issue of gradient disappearance and reduce the no.of parameters etc.

D. GoogleNet

It is a 22 layers model, which uses around 24 millions parameters with better performance than predecessors. It achieved lowest top 5 error rate of 6.67%.

E. ResNet

Residual Network is any kind of advanced version of CNN with additional layers addition. It allows us train DNN upto 150+ layers successfully. Various variations of RestNet according to number of layers are- ResNet 18, ResNet 34, ResNet 50, ResNet 101, ResNet 110, ResNet 152, ResNet 164, ResNet 1202. ResNet 10 actually replaced VGG 16 very faster.

F. MobileNet

It is a 53 layers model which is a eficient CNN for mobile applications. MobileNets are generally small in size, has low latency and low power. With MobileNet large size images gives better performance, it support input size of more than 32x32.

G. InceptionV3

It developed by Google that support three types of filter sizes: 1x1, 3x3, 5x5, max pooling, around 1 millions param- eters and performed 78.1% accuracy on ImageNet dataset.

H. RNN (Recurrent Neural Network)

These are robust type and powerful neural networks which useful in temporal dynamic or sequential data like audio, vedio, time series, speech, weather etc. LSTP (long short-term memory) networks are special type of RNN which capable of handling long term dependencies.

4. Literature Survey

[1] It's a survey of CADs system, and mainly focused on findings for further improvements in CADs. In this study author discussed that the CAD system can be implement for unsupervised ML algorithms to classify the images for improving performance of CADs.

According to a case study [5] of the American College of Radiology (ACR), defined that the breast density has an impact on mammography. In [6] they compared various DL methods, and also concluded that MRI can be a cause of allergy in patient. By comparing various DCNN [6] the maximum result of MLP (Multilayer Perceptron) algorithm has 99.04% which classify data into two classes as benign or malignant. In [7] they defined that some DCNN i.e., Pix2pixHD gives 27.67% precision & 44.51% sensitivity; GGGAN gives 44.77% pre- cision & 68.21 sensitivity%; MSE gives 30.28% precision & 38.15% sensitivity; GGGAN-VGG gives 46.83% precision & 75.14% sensitivity, FFDM gives 50% precision & 83.24% sen- sitivity and Re-projection gives 43.21% precision & 67.63% sensitivity on combination of DBT and FFDM images. They concluded their result with 1077 cases of malignant and col- lected 122 cases independently. With the concept of DCNN by using MIAS (Mammogram Image Analysis Society) dataset, ConvNet model [8] provides 97% accuracy but limitation is of high false +ve ratio. MIAS is a small database included with noise and low-resolution images.

[2] With DL-CAD (deep learning-CAD) achieved 92% accuracy. In this study, they discussed a complete comparison among various deep learning methods on different data sets of different screening techniques as tabular form. In [13], InceptionV3, DenseNet21, ResNet50, VGG-16 and MobileNet applied on MIAS, DDSM and CBIS-DDSM datasets which classify the data into two class. They also proposed a modified U-Net for segmentation and augmentation on DDSM images and then applied InceptionV3, DenseNet21, ResNet50, VGG-16 and MobileNet. There InceptionV3 achieved maximum result which is accuracy-98.87%, sensitivity-98.18%, AUC-98.88%, precision-78.79%, F1-score-97.99.

[17] proposed a Conditional Generative Adversarial Network (CGAN) on RCDT images, where they used magenta-green fusion for making difference between images. And RCDT images defined in two ways as real and simulated groups. Then VGG-16 CNN performed on fused, real and simulated RCDT images which gives AUC-0.77 with 95% CI of [0.71, 0.83] in CNN fused, AUC-0.70 with 95% CI of [0.64, 0.77] in real CNN and AUC-0.68 with 95% CI of [0.62,0.75] in simulated CNN. They removed some VGG layers for preventing over fitting, concluded that CNN- fused is better than CNN real or CNN simulated.

[10] proposed a new type of classifier TV-CNN (two view-CNN) by combining CNN and RNN on DDSM with 94.7% accuracy, 94.1% recall, 96.8% AUC and it classifies the images in benign and malignant. They combined residual block with convolution as a base classifier Convolution NN and feature fused by using GRU (gate Recurrent Unit). According to [18] an advance deep CNN model achieved performance 88% compare to performance of ResNet with 81.5% which defined abnormalities in breast into four classes as: masses, calcification, carcinomas and asymmetry. But it has over-fitting problem, therefore it cannot use for complex data. However, most of the classifier divided the images into two classes but more classes can be introduced by using other features.

Another CAD [19] system by using FFDM images achieved 92.9% accuracy with temporal subtraction which is 7% more than that of temporal analysis (85.7% accuracy). It proved that the temporal subtraction can achieve better performance and this CAD system extracted 28 feature which further classified into four categories-shape, intensity, First-Order Statistics (FOS) and Gray Level Co-occurrence Matrix features (GLCM). ResNet50 with ADAM optimizer in [12] trained model for 2D and 3D images, 2D images classified as 0 or 1 and 3D images classified by taking result from 2D model. This model learned with learning rate from 0.000001 to 0.00001 and database created from DDSM, OMI-DB, US clinical sites (site-A, site-B, site-C, site-D, site-E) which gave AUC: 0.957 ± 0.010(0.959± 0.008 using all negatives) and avg specificity: 69.9%. [11] developed a deep learning CNN to segment and classify various types of breast abnormalities using SVM. Primary prevention of breast cancer is to identify the cause like BRCA1, BRCA2 and TP53 gene mutation. Unlike existing studies which classified cancer into two classes, it is the model

Table 2
Performance analysis based on methodology and parameters

Publication	Methodology	Accuracy, Sensitivity, Specificity	AUC
S.Bagchi, et al. [1]	CADs	95%	-
S. A. Chikarmane, et al. [9]	FFDM, DBT	DBT- 97%FFDM- 97%	-
H. Li, J. Niu, et al [10]	ResNet	94.7%	0.968
H. D. Quy, et al. [11]	DenseNet121, DenseNet169, DenseNet201	DenseNet121: 97.64%, 99.21%, 94.44% DenseNet169: 98.03%, 99.02%, 96.03% DenseNet201: 98.16%, 98.82%, 96.82%	98.87%, 98.98%, 98.79%
W. Lotter, et al. [12]	CNN (ResNet-50) & Adam	-, -, 69.9%	0.957
W.M. Salama, et al. [13]	Automated CNN	98.87%, 98.98%, 98.79%	0.988
C. Zhang, et al. [14]	DenseNet (A-Normal & abnormal and B-Benign & malignant)	A-94.92%, 96.52%, B-95.24%, 96.11%	A-0.95 & B-0.95
S. J. S. Gardezi, et al. [15]	VGG 16	98%	1.0
S. Shakeel, et al. [16]	AlexNet	88.7%	0.885

Table 3
Literature survey based on methodologies, datasets and parameters

Publication	Database	Methodology Used	Data Source	#Classes	#Images	Image Size
S. Bagchi, et al. [1]	MIAS	various CAD system	kaggle	2	322	1024x1024
S. A. Chikarmane, et al. [9]	FFDM (5706 examinations 4091 patients), DBT (4440 examinations 3647 patients)	FFDM, DBT	Clinical data	-	-	-
H. Li, J. Niu, et al. [10]	DDSM	ResNet	kaggle	3	2620	299x299
H. D. Quy, et al. [11]	Subset of INbreast Database (PNG Images)	DenseNet Model- DenseNet121, DenseNet169, DenseNet201	kaggle	-	410	224x224
W. Lotter, et al. [12]	DDSM, OMI-DB, US clinical sites	CNN (ResNet-50) & Adam	-	2	-	-
W. M. Salama, et al. [13]	MIAS, DDSM, CBIS-DDSM	Automated CNN	kaggle	2	MIAS-322, DDSM-564, CBIS-DDSM-330	-
C. Zhang, et al.[14]	DDSM	DenseNet (A-normal & abnormal and B-benign & malignant)	kaggle	3	10,480	512x512
S. J. S. Gardezi, et al. [15]	IRMA	VGG-16 wtih KNN&SVM	kaggle	2	1733	224x224
S. Shakeel, et al. [16]	DDSM-BCRP, INbreast	AlexNet	github	2	-	224x224

improved disease management and classify four classes and has 88%accuracy. Four classes are: 1. masses, 2. calcifications, 3. carcinomas and 4. asymmetry mammograms.

They applied pre-trained ResNet50 to overcome over-fitting models. And introduced enhanced deep CNN model by varying learning rate. This model may perform better with additional layers or by using other optimizer i.e. ADAM or any other advance optimizer.

5. Performance Parameters

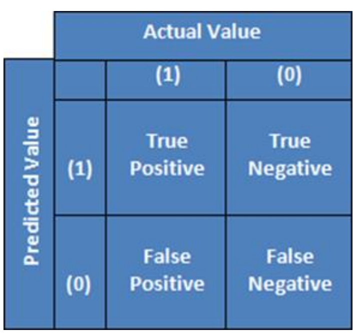

Fig. 4. Confusion matrix

Where, TP (True Positive)-Patient has cancer that were correctly identified by algorithm; TN (True Negative)-Patient did not have cancer that were correctly identified by algorithm; FP (False Positive)- Patient has cancer but algorithm said they didn't; FN (False Negative)- Patient do not have cancer but algorithm says they do.

a) *Accuracy:* Actually, right result by the algorithm.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

b) *Sensitivity (recall):* Rightly identified by algorithm from actual right and also mentioned with TPR (true positive rate).

$$Sensitivity = \frac{TP}{TP + TN} \tag{2}$$

c) *Specificity(Precision):* Rightly identified by algorithm from the total of actual right identified by algorithm also termed as positive predicted value (PPV). It very Useful for spam detection.

$$Specificity = \frac{TN}{FP + TN} \text{ or } \frac{TP}{TP + FP} \tag{3}$$

d) *F1-Score:* Also called harmonic mean of sensitivity (recall) and specificity.

$$F1Score = \frac{2 \times Sensitivity \times Specificity}{Sensitivity + Specificity} \tag{4}$$

e) *Receiver Operating Characteristic (ROC) Curve:* Plotting a graph by using TPR (true +ve rate) and TNR (true -ve rate) is called ROC.

f) *Area Under the Curve (AUC):* It measures the degree of separability in entire two-dimensional area and represent the total area under ROC curve.

g) *Confidence Interval (CI):* It represents the statistics of a parameter fall between pair of values around the mean value. Basically, the mean of our estimated value to the variation in estimate.

6. Conclusion and Future Scope

Conclusion: Through this study we have discussed about the performance of various breast cancer screening techniques, available data sets and deep CNN methods. We found, there is a limitation of limited data available for every type of breast cancer abnormality which is a challenge for multi-class classification of breast cancer. And another challenge is result variation with density of breast and age of patient. In Table.1 performance of various screening methods have discussed based on several parameters. Whereas, Table.2 summarized the performance of different deep learning methods and Table.3 is a tabular summary of data sources, models, #classes, #images and image size they have used.

Technology defined that CADs are helping doctors as 2nd assistant, and presently DL-CADs (Deep Learning CADs) as advancement to classify the image for improving performance of the CAD system. If we have large amount of data with high quality, it can improve the performance of DL-CAD. Because Deep CNN is very useful to classify mammograms for detecting cancer at very early stage. But with respect to DL-CAD there are various challenges to be considered are:

- limited data and over-fitting problem.
- blurred boundaries, shadow, attenuation, speckle interference, low contrast images.

Future Scope: So much work has been already done on classification of breast cancer into two classes as benign and malignant, but multiple classes can be classified as breast cancer abnormalities which can be very helpful to detect cancer at very early stage. Therefore, there is a requirement of enhanced CAD/DL-CAD systems.

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