Predictive Diagnosis of Breast Cancer Using Deep Neural Network

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ABSTRACT

The ultimate aim of the study was to predict the overall survival rate for women affected by breast cancer by developing and validating a prognostic model. In this study mammography image were collector and the health records for at least 1 year before mammography. The algorithm was trained on mammogram and health records of women to make two breast cancer predictions: (i) to predict biopsy malignancy and (ii) to differentiate normal from abnormal examination. In this model, ANN's were used to complete the task. This model was developed using a large proportion of concealed layers for the data generalization. A large proportion close to a 1000 mammography records and results were used in the model to differentiate between benign and malignant tumors. Before being inputted, all the data was inspected by radiologists. The accuracy of the model was determined to be an AUC of 0.96 and was a huge success (area or curve used to determine the success of model). This model is highly consistent, effective and less prone to error when compared to diagnosis performed by pathologists. The study obtained very high accuracy of predictions such as 93% and 95%. This facilitates early and accurate diagnosis of breast cancer for patients and early diagnosis is integral in cancer diagnosis. This also contributes as a useful tool for new selective drugs for these tumors to be treated. In Today World, Technology has facilitated great improvements in various important aspects of the world such as healthcare, agriculture, business etc. Despite this tremendous growth and improvement various diseases are still on the rise world wide. Among these Cancer stands as one of the major causes of death and accounts for about 9.6 million deaths world wide. Cancer has various forms. Among which Breast Cancer is one of the most dangerous and common reproductive cancers that mostly affects women. According to the World Health Organization, Breast cancer affects about 2.1 million women every year. In order to improve Breast cancer outcome and survival, Early detection is critical. Hence, the goal of our project is to use Machine learning techniques and deep learning to increase the proportion of breast cancers identified at an early stage, allowing for more effective treatment to be used and reduce the mortality rate. Since early detection of cancer is key to effective treatment of breast cancer, we use various machine learning and deep learning techniques to predict if a tumour is benign or malignant, based on the features provided by the data in a more accurate, consistent and less prone to error.

KEY WORDS: BREAST CANCER, WORLD HEALTH ORGANIZATION, 2.1 MILLION WOMEN EVERY YEAR.

INTRODUCTION

The occurrence of mutations which are changes in genes regulating the growth of cell causes the deadly disease Cancer. This causes the multiplication and division of cells in an uncontrollable fashion. The cancer developed in the breast region is defined as breast cancer. The formation of cancer takes place in the duct or lobules of breast.

The milk-producing glands are termed as lobules and the milk transportation pathways to the nipple from the glands are known as ducts. Occurrence of cancer can be extended to the connective fibrous and fatty tissue of the breast. The affected cancer tissue has the dangerous ability to affect other healthy tissues and also spread or travel to the lymph nodes in the arm. The movement of the cancer cells to the rest of the body parts is facilitated by the lymph nodes.

Machine learning (ML) and its techniques have recently provided great results in the healthcare field. Although Machine learning models are not new and have been increasingly used to analyse data in health care, Machine learning can be used to diagnose breast cancer at a level equal to pathologists and hence acceptable in clinical practice as a very useful tool. The purpose of our study is to use Machine learning and deep learning for early breast cancer prognosis and assess its stage and survival rate of the patient. Analyse data in health care, A machine learning can be used to diagnose breast cancer at a level equal to pathologists and hence acceptable in clinical practice as a very useful tool. The purpose of our study is to use Machine learning.

Breast Cancer: The cancer occurred and developed in the region of the Breast is termed as breast cancer. Typically, Breast cancer occurs in women and also in men in rare scenarios. It is one of the most prevalent and deadly diseases around the world. It is said to commonly occur in women between the age group 40-55 years old. Breast cancer is said to initiate with cells in the breast growing in an uncontrollable manner. Early diagnosis and treatment is key in breast cancer.

Symptoms: One of the dangerous attributes of breast cancer is that close to no symptoms are visible during its early stages. There are many scenarios in which the tumor being very small can be neglected. However, the abnormality can be identified on a scan or mammogram. When the tumor is first felt it mostly means a new one formed in the breast which was initially absent. But, all tumors in the breast are not a tumor caused by cancer. A variety of symptoms are caused due to each kind of breast cancer. Most of these symptoms are similar in character, but there are few symptoms which are distinct. The common symptoms of breast cancers include:

- A lump in the breast developed recently and may or may not cause pain.
- Pain in breast region
- Skin turning red in the breast
- swelling in breast region
- discharge from nipple except breast milk
- discharge containing blood from nipple
- Skin flaking or peeling nipple or breast region.
- Change in size or shape of breast which takes place suddenly.
- Nipple inversion
- Appearance changes on breast region
- Under arms swelling

Types of Breast Cancer: The common types of breast cancer are as follows:

In situ Cancers: This type of cancer does not spread to other regions and stays in the region of initial development.

Ductal carcinoma in situ (DCIS): The carcinoma at the very initial stage (stage 0). The cancer hasn't spread and in its initial region of development. However, if untreated this may become dangerous. This stage of cancer is easily curable. Lobular carcinoma in situ (LCIS). This carcinoma originates exclusively in lobules producing milk. It isn't termed cancer but has the ability to develop into breast cancer in the future. Regular medical check-ups are mandatory.

Invasive Cancers: These are dangerous and have the ability to grow and spread across the body.

Invasive or infiltrating ductal carcinoma (IDC): This originates in the ducts producing milk and grow and damage the surrounding cells and tissues in the breast region by breaking the walls. It is highly prevalent and accounts for a greater margin of deadly cases.

Invasive lobular carcinoma (ILC): This originates in the lobules and spreads to the other parts. It accounts for about a lesser margin of deadly breast cancers.

Breast Cancer Risk Factors: The reason and cause of breast cancer is yet to be identified. But, the probability of occurrence can be determined by some factors such as age, genetic factors, personal health history, and food habits contribute to them. The factors of risk are classified as controllable and uncontrollable risk factors.

Breast Cancer Uncontrollable Risk factors:

- Age: Women below the age are less likely to be in risk and women above age 50 are prone to the disease.
- Dense breasts: Presence of more connective tissue than fatty tissue can reduce the visibility of tumors in the breast in scans.
- Personal history of cancer: This plays a major role as previous breast cancer patients are more prone to recurrence of the disease.
- Family history: If a close blood relative had breast cancer, you're more prone to the disease.
- Genes: Mutations or change in genes may cause this disease. Especially genes such as BRCA1 and BRCA2.
- Menstrual history: A patient is more prone to breast cancer if:
 1. Early periods initiation before the age of 12.
 2. Periods don't stop until age 55.

Breast Cancer Stages

- Early stage (stage 0) or non-invasive breast cancer. The presence of the disease is completely limited to its place of origin and cause no symptoms.
- Stage I breast cancer. The tumor or cancer is very

small in size and doesn't spread but stay in its original position.

- Stage IIA breast cancer. The tumor is:
- less than 2cm with development in underarm.
- Bigger than 2cm and smaller than 5cm with no development any where else.
- Stage IIB breast cancer. A tumor that's:
- A big tumor of 5cm in size without any development in any other region.
- A big tumor in size with development in the other regions across breast.
- Stage IIIA breast cancer or locally

advanced breast cancer:

- A large tumor in size and spread across the region of breast such as lymph nodes under the arm.
- A cancerous tumor that spreads to surrounding tissues.
- Stage IIIB breast cancer. A tumor which spreads across the chest.
- Stage IIIC breast cancer. A tumor which has rapidly spread and includes development in lymph nodes
- Stage IV (metastatic) breast cancer. A tumor which rapidly spreads from its place of origin to other parts of the body and is very dangerous.

MATERIAL AND METHODS

Dataset: The dataset consists of 292,624 mammography examinations screened digitally from close to 2 lakh patients. The examination distinctly includes minimum 4 images which were a part of the mammography screening. The four images are as follows: L-CC (left craniocaudal), R-CC (right craniocaudal), L-MLO (left mediolateral oblique) and R-MLO (right mediolateral oblique). The reports obtained from the pathology department were used in the process of determining the labels which designate whether the tumor in the breast denotes malignant tumor or benign tumor.

In a period of 140 days of mammogram screening close to 5000 examinations accompanied by a minimum of one biopsy was performed. It was found that 980 (8.2%) were found to be malignant cancers and close to 5000(47%) were determined to have benign cancer and the remaining 200(20%) were determined to have both benign and malignant cancer. The proportion remaining that failed to match with the results of the biopsy, were labeled as malignant and benign tumours absent in both breasts. The examinations which were found to be matching with the results of biopsies, were provided to pathologists and radiologists to determine at pixellevel placement or place of origin of the biopsied lesions. It was then determined by the specialists that about 32% of the examinations were concealed and failed to be visible or found on mammography and could be determined of their presence using other imaging techniques such as: MRI or Ultrasound.

METHODOLOGY

Adaptive mean filter has been used to remove noise from

image. Since it is better among all the spatial filters and distinguish fine details from noise. The Adaptive Median Filter is used to determine the noise impulse affected pixels in an image by spatial processing. The pixels are classified by adaptive mean filters as noise by comparing each pixel in the image to its surrounding neighbor pixels. The size of the neighborhood is adjustable, as well as the threshold for the comparison. A structurally disjoined pixel to its similar pixels and greatly varying from a maximum of the pixels surround it is designated as impulse noise.

The median pixel value is then exchanged by the noise pixels in the surroundings where pixels have already passed the noise labelling test. Initial conversion of the image into grayscale image using `rgb2gray()` function which is followed by the application of adaptive mean filtering to the resulting image and then finally converting the image into unsigned integer 8 using `uint8()` function. In this manner the image is preprocessed and followed by performing GMM segmentation (Gaussian Mixture Model) on the preprocessed image with 2 regions and 2 components GMM components 2 and maximum number iterations 10. we performed k-means segmentation.

with $k=2$. then we Implemented HMRF-EM (Hidden Markov Random Field Model) and its Expectation-Maximization Algorithm.

Block Diagram

Figure 2.A: Diagrammatic representation of breast cancer examination classification as a learning task.

Deep CNNs for cancer classification: Two primary binary labels were designated for every breast under examination: malignant tumor present/absent in the breast region, and the benign tumor presence/absence

in the breast region. Taking into account both the sides of the breast, left and right every examination consists of four labels. Our ultimate goal is to construct four distinct predictions which are attributed to the four distinct labels corresponding to every examination. The four High resolution images are in agreement with the views of the four mammography screening are taken as the input. Every image is cropped to a fixed size of 2767×1924 pixels for CC views and 2947×1784 pixels for MLO views.

Model Architecture: We trained a deep multi-view CNN of architecture. There are 2 core modules in the overall network:

1. Four columns four view-specific, each based on the ResNet architecture that outputs a fixed-dimension hidden representation for each mammography view,
2. Mapping of the calculated concealed representations to the final predictions using two completed and connected layers. The calculation of 256-dimension concealed representation vector of every view was performed using Resnet-22. The weights were shared by columns applied to L-CC/R- CC. This was also followed and weights were shared by columns applied to L-MLO/R-MLO. This step is followed by the concatenation process of L-CC and R- CC representation into a 512 dimensional vector, and the generation of predictions of the four outputs are achieved by application of two completely connected layers. This process is repeated for the successive L- MLO and R-MLO views. The final output and predictions are deduced by using the average probability of CC and MLO branches of the model.

Fig.3. Architecture of our model. Four Res Net-22 columns take the four views as input. The architecture is classified into two branches called CC and MLO. In each branch, the corresponding right and left representations from the ResNets are individually average- pooled spatially and concatenated, and two fully connected layers are applied to compute the predictions for the four outputs. The predictions are averaged between the CC (craniocaudal) and MLO (mediolateral oblique) branches. Weights are shared between L- CC/RCC columns and L-MLO/R-MLO columns. The first layer of the columns are modified in accordance to inputs as additional channels are added to the heatmaps.

Experiments: For each and every experiment, the training set is used for optimization of parameters of our model and the validation set and the training procedure. Unless in any other cases specified, the results are computed throughout the screening population. To acquire, test sample prediction for each sample we applied random transformations for input 10 times, applied the model to 10 of the samples each separately and then average the 10 predictions (in SI details). To improve our results further, we used the technique of model ensemble [19], wherein the predictions of various different models are averaged to produce overall prediction of the ensemble. In our case, we trained 5 copies of every model with different random initializations of the weights within the fully connected layers. The pre-trained model's weights are used to initialize the remaining on BIRADS classification, it gives our model a significant boost in performance. For each model, we report the results from a single network and from an ensemble.

Test Populations

In the experiments, to test the various hypothesis we evaluate our model on several populations:

1. screening population, it includes all exams from the test set without sub sampling;
2. biopsied subpopulation, which is subset of the screening population, and includes the exams from the screening population containing breasts which underwent biopsy;
3. reader study subpopulation, consists of the subpopulation of the biopsied report and randomly sampled subset exams from the screening population without any findings.

Evaluation Metrics: The models were initially evaluate in terms of AUC (area under the ROC curve) for malignant or not malignant and benign or not benign classification tasks on the breast level. The model and readers' responses on the subset for reader study are evaluated in terms of AUC and precision-recall AUC (PRAUC), which are the regularly used evaluation metrics of the performance of the radiologists.

The different aspect of predictive model performance is captured by ROC and PRAUC. The ROC curve summarizes the trade-off between the true positive and false positive rate for a model using probability thresholds. The true positive rate and positive predictive value is summarized

by the precision recall curve for a model using different probability thresholds.

Figure 4: AUCs for patients grouped by age and by breast density

Results across ages and breast densities: We split the test data by patient age, breast density and evaluate the model for each and every subpopulation (Fig 4). The performance of the image-only and image- and heat maps model varies based on age. We also find that both models perform worse on dense breasts i.e. in “heterogeneously dense” and “extremely dense” than on fatty ones which are almost entirely fatty, which is consistent with the decreased sensitivity of radiologists for patients with dense breasts. Differences between the model’s performance whether its benign/notbenign classification is larger than in malignant/not malignant classification. We conclude that this is due to age and the level of noise is influenced by the breast density in benign/not benign labels, associated with radiologists confidence in their diagnoses.

Literature Survey

S.N O	NAME OF THE PAPER	AUTHOR	DATE OF ISSUE	INFERENCE
1.	Curvature-based Selection of Feature by applying in Classification of Electronic Health Records	Zheming, Jie Li, NouraMoubayed.	10 January 2021	Curvature-based Feature Selection method - lack of expert knowledge of clinical science, visualisation the results of feature ranking of the proposed CFS to support better explainability.
2.	Deep Neural Networks Performance in Screening of Breast Cancer.	Nan Wub, Jason Phangb, Jungkyu Parkb	20 March 2019	Deep convolutional neural network; AUC of 0.895; high accuracy-two-stage training procedure, which allows them to use a very high-capacity patch-level network to learn from pixel- level labels alongside a network learning from macroscopic breast-level labels.
		Habib Dhahri	3November 2019	Geneticprogramming technique for feature selection and selection of parameter values of classifiers of machine learning. The Performance was based on sensitivity, specificity,precision, accuracy.
4.	Prediction and detection of breast cancer using machine	Anoy Chowdhury	19 June 2020	breast cancer tumour predictor on the Wisconsin dataset and created graphs and results for the sam.e Selection of appropriate algorithms with good home dataset will lead to the development of prediction systems. Proper diagnosis of patients suffering from breast cancer can be sured using the sesystems.
5.	Applications of Machine Learning in Cancer	Joseph A, David S.	2006	From this paper it is concluded that machine learning methods

	Prediction and Prognosis			can be used to substantially (15-25%) improve the accuracy of Predicting cancer susceptibility, recurrence and mortality.
6.	Machine learning methods for Breast cancer diagnostics	Shahnorbanun, Ashwaq Qasem.	29 January 2018	This paper deals with two most popular techniques that use machine learning (CADe & CADx). False positive rate is reduced significantly using this method and rapidly improves the prediction performance of breast cancer.
7	Using Machine Learning Algorithms for Breast Cancer Risk Prediction and Diagnosis.	Hiba Asria	2016	In this paper, they have employed four main algorithms: SVM, NB, k-NN and C4.5 on the Wisconsin Breast Cancer (original) datasets; Compared efficiency and effectiveness of those algorithms in terms of accuracy, precision, sensitivity and specificity to find the best classification accuracy; SVM reaches accuracy of 97.13% and outperforms other algorithms.
8.	Early Detection of Breast Cancer Using Machine Learning Techniques.	Bashari Rad	September 2018	Breast cancer And ML; introduced in-depth literature review on Existing ML methods; Suggest that SVM- most popular method used for cancer detection applications.

DISCUSSION AND CONCLUSION

A large number of training sets based on breast level and pixel level labels are added to build a neural network for breast cancer classification on screening exams. The significant success is due to the amount of computation encapsulated in this model, that had been densely applied to the input images as an additional input channel to breast level model. The training to the model would be impossible with the current available hardware. Even though our results are promising, we suggest the test set used are relatively small and are advised to require further clinical validations. We also acknowledge that our performance is much stronger than that of the specific task performed by radiologist.

Screening mammography is just the beginning step in the pipeline of diagnosis, further requiring the radiologist's final decision for another process and decision to biopsy after considering the mammography images and possible ultrasound. In our study, the hybrid model outperformed both the neural network and expert radiologist suggestion, suggesting that the use of model like this could improve radiologist sensitivity for breast

cancer classification and detection. Contrastingly, our model design is relatively simple. and with our model it is possible to develop more sophisticated and accurate models. Moreover, the prediction based on whether the patient had any visible cancer at mammography exam is the most simplest possible way of prediction among others. In addition to testing the model in real-time analyzing of screening mammograms, a transparent next step would be predicting the development of breast cancer in the future—at the earliest before it is even visible to a naked human eye and symptoms are well shown.

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