Breast Cancer detection using Deep learning techniques

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***Abstract*—**

I. Introduction

Human body is made up of hundred thousands of cells. They provide structure for the body. When these cells get old or abnormal they die. Cancer develops in a human body when this process gets disrupted and also due to multiple changes in the genes. These cells start growing uncontrollably and form a mass called tumor. This cancerous tumor is again of two types malignant and benign. A benign cancerous tumor is a type of tumor which does not spread to other parts of body and a malignant tumor is which spreads to other parts of body is sometimes not curable. Carcinoma is a type of cancer that starts in cells that is made up of the skin or tissue lining organs. Breast cancer is a carcinoma type of cancer. It starts in the breast. It can be either one of the breasts. It most probably occurs in women and rarely men. Majority of the time breast cancer is not malignant. About 1 in 8 U.S. women will develop invasive breast cancer over the course of her lifetime. In 2022, an estimated 287,850 new cases of invasive breast cancer are expected to be diagnosed in women in the U.S.These occur due to genetic mutations that happen as a result of the aging process and life in general, rather than inherited mutations.[1] Many methods also available such as mammography, ultrasound, CT and MRI. Mammography is the most widely used screening method[2].Since, a lot of women are diagnosed with breast cancer our main motive is to develop a method which can efficiently detect breast cancer at an early stage. We intend to do this using Computer-aided detection using various deep learning techniques.

Screening Mammography:
The process of using low energy X- rays to examine the human breast for screening and for discovery of Breast cancer at an early stage through mass characteristics is called mammography screening. For creation of images mammograms uses doses of Ionizing Radiation [13]. It uses low energy x-rays like Mo and Rh than the rays which are using in some of the methods like Radiography, Ductography, Positron emission mammography, Magnetic resonance imaging [13] and ultrasounds [13]. But ultrasound imaging is further used in mammography for the detection of palable masses which can't be found by mammograms. There are different image screening techniques are being using for the detection of cancer like Digital breast tomosynthesis [14] which is reliable and used to provide higher diagnostic accuracy [14] and Diffuse optical mammography [5] which is used to investigate breast composition through spectral analysis. The radiologists who examined the mammography chooses the best category that describes the breast density. The breasts are almost entirely flatty and are extremely dense which makes hard to see the tumors during the mammograms [15].

Computer Aided detection for screening mammograms: Radiologists are looking for computer algorithms which not only increase detection rates of different medical conditions, but which are also cost effective and efficient. One specific way of detecting breast cancer is by using Computer-aided detection (CAD).CAD can double check,thus replacing traditional double reading by a second radiologist[4]. CAD is used for scanning digital mammograms and marking all the areas that indicate cancerous features. Radiologists generally review these marks after making their own interpretations and compare the two to reach a final assessment of the image [3]. Even-though such a technology might seem appealing, but the output obtained by using CAD can sometimes be controversial too. A large clinical trial in the United Kingdom has shown that single reading with CAD assistance has similar performance to double reading [8]. However, in the last decade multiple studies concluded that currently used CAD technologies do not improve the performance of radiologists in everyday practice in the United States [16-18]. From the above cases, we can conclude that CAD systems need to be improved before using them in everyday practice.[7].
Currently used CAD approaches are based on describing the X-ray image with meticulously designed hand-crafted features, and machine learning for classification on top of these features [5,6,7]. However, the Deep learning CNN models can solve problems which might be harder to solve using the traditional CAD systems. These models learn from complex data, perform image recognition, image enhancements and medical diagnosis. Hence, using these techniques might help radiologists get accurate results and predictions. Several studies have attempted to apply Deep Learning to analyze mammograms [9-12], but the problem is still far from being solved [7].

II. Methods

A. Dataset

This dataset consists of images from the CBIS-DDSM [3] datasets. The images have been pre-processed and converted to 299x299 images by extracting the ROIs. The following dataset contains a total of 55,890 training examples. Out of these examples, 14 (percent) are positive and remaining 86(percent) are negative. We have used the MIAS Dataset,which containes different columns like Character of background tissue, Class of abnormality present,Severity of the abnormality,x,y image-coordinates of centre of abnormality and Approximate radius (in pixels) of a circle enclosing the abnormality.The size of all the images is 1024 pixels x 1024 pixels. The images have been centered in the matrix. When calcifications are present, centre locations and radii apply to clusters rather than individual calcifications. Coordinate system origin is the bottom-left corner. In some cases calcifications are widely distributed throughout the image rather than concentrated at a single site. In these cases centre locations and radii are inappropriate and have been omitted.

Data Availability

The CBIS-DDSM dataset was obtained from: https://wiki.cancerimagingarchive.net/display/Public/CBIS-DDSM

This CBIS-DDSM (Curated Breast Imaging Subset of DDSM) is an updated and standardized version of the Digital Database for Screening Mammography (DDSM) . The CBIS-DDSM collection includes a subset of the DDSM data selected and curated by a trained mammographer. The DDSM dataset is available on: http://marathon.csee.usf.edu/Mammography/Database.html.

Pre-processing the Data The dataset consists of negative images from the DDSM dataset and positive images from the CBIS-DDSM dataset. The data was pre-processed to convert it into 299x299 images. The negative (DDSM) images were tiled into 598x598 tiles, which were then resized to 299x299. The positive (CBIS-DDSM) images had their ROIs extracted using the masks with a small amount of padding to provide context. Each ROI was then randomly cropped three times into 598x598 images, with random flips and rotations, and then the images were resized down to 299x299. The images are labeled with two labels:

labelnormal - 0 for negative and 1 for positive

label - full multi-class labels, 0 is negative, 1 is benign calcification, 2 is benign mass, 3 is malignant calcification, 4 is malignant mass.

B. Methodology

R-CNN stands for Regional Based Convolutional Neural Network. It is a machine learning model used for object detection. We use R-CNN to detect object in a given image. It combines the rectangular region proposals with convolutional neural network features. It is basically a two stage algorithm. In the first stage the image is divided into regions where there is a probability to find a object. In the second stage it classifies the object in the region accordingly. The Faster R-CNN detector adds a region proposal network (RPN) to generate region proposals directly in the network instead of using an external algorithm like Edge Boxes. The RPN uses Anchor Boxes for Object Detection. Generating region proposals in the network is faster and better tuned to your data The Faster R-CNN model builds on the Fast R-CNN model. A region proposal network is added to produce the region proposals instead of getting the proposals from an external algorithm [19].Selective search method is used in Faster R-CNN along with RPN.

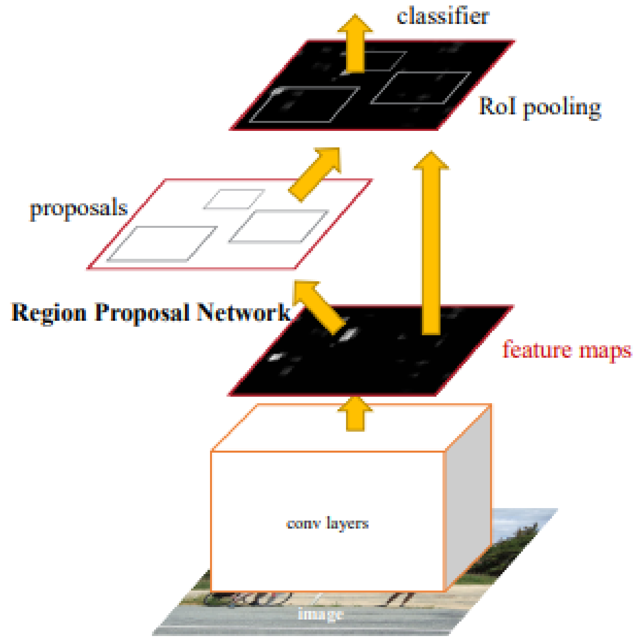

Fig. 1. Diagram of Faster R-CNN model for CAD in mammography

It is mainly divided into the following parts in structure: The Convolution layer which can extract the feature map of the entire picture. Next is the Region Proposal Network (RPN) which is the core part of Faster R-CNN, RPN uses the Selective Search method which is used in Fast R-CNN algorithm to create a region proposal. Using this RPN to obtain a region proposal can be more quickly and efficiently use the CNN network. RPN generates anchors while generating a region proposal. The judgement function determines whether the anchors are foreground or background, and then adjusts the anchors through border regression to obtain an accurate region proposal. RoI pooling: It can deal with the problem that different sizes of feature maps input to the network with fully connected layer. The fixed size is obtained by up-sampling. The classification layer is responsible for judging which class an object belongs to and the regression layer adjusts the positions of regions of interest (RoIs) to obtain the final object detection result [20]. The model proposed has a VGG16 network, which is 16 layer deep CNN[21]. The last layer detects whether the image has malignant or benign lesions. The model gives a box for each lesion that it detects and gives is score which tells how confident the model is about the lesion detected. If there is a case of multiple images of the breast of the same patient then we take average scored of each image. This model has used joint optimization which means using optimized object detection part and classifier part at the same time, during training. Vertical and horizontal flipping is also applied to the dataset. We will be using Google collab as our development environment.

C. Visualizing the Dataset

We performed an exploratory data analysis just to get familiar with the datasets that we are using for this paper. The main motive of this was to get to know what exactly are data looks like and what are the different fields of the datasets that are present which might prove helpful while we train and test the data. The results that we got from the data analysis were as follows:

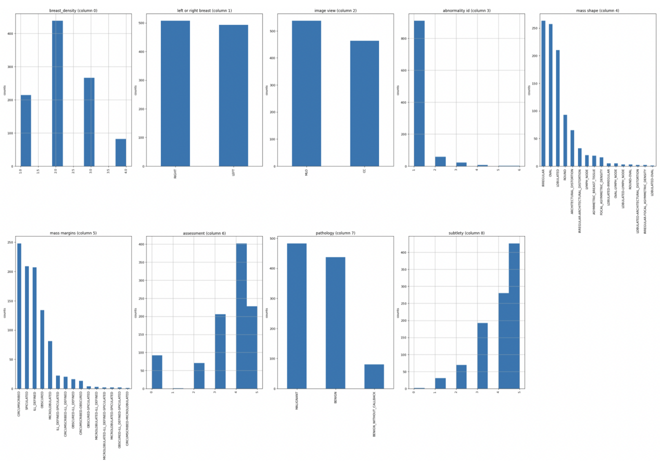

Fig. 2. Scatter and density plot of different columns like breast density, image view, abnormality-id, mass margins, assessments, subtlety of CBIS-DDSM Dataset.

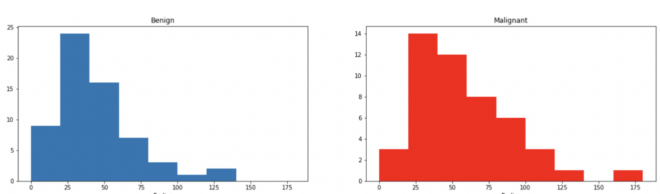

Fig. 3. Bar Graphs showing the radius density of benign and malignant masses of MIAS dataset.

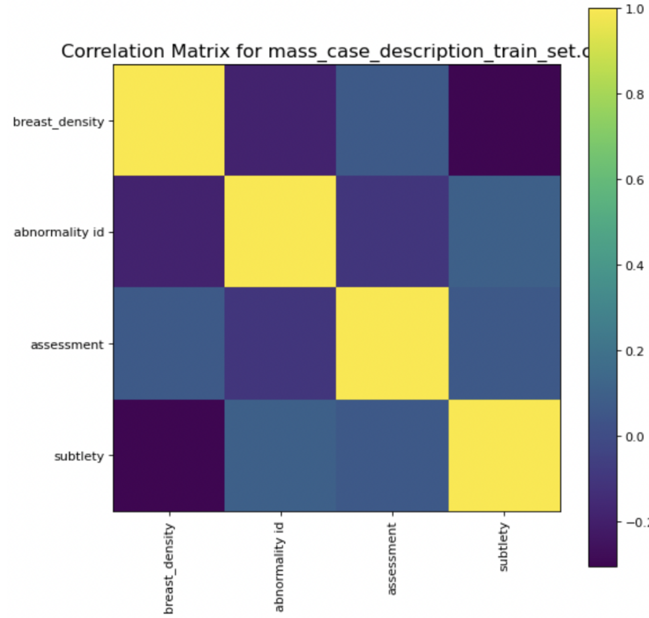

Fig. 4. Co-relation Matrix for mass-case description of CBIS-DDSM dataset.

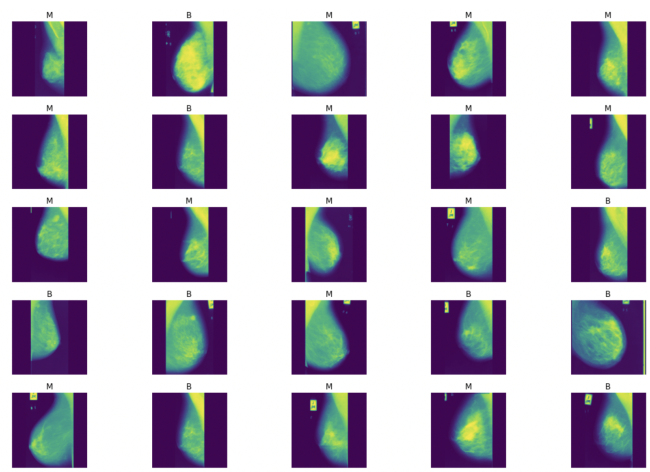

Fig. 5. Randomly scanned 25 images of left and right breasts of MIAS dataset.

III. Results

We have worked on, to predict the breast cancer using deep learning techniques. Mammograms are commonly used to screen for breast cancer. For this we have implemented the Convolution Neural Network which is a deep learning neural technique since they have a huge breakthrough in image recognition. For training the dataset we used two methods like segmentation and classification for detecting metastatic breast cancer using whole slide images of sentinel lymph node biopsies. We performed this method on the selected dataset, and we compared the networks with pre-defined weights in the first step. And in the second step we trained whole image classifier from patch classifier. We have compared the results between CNN and Faster R-CNN. We have trained the datasets accordingly and executed on the CBIS-DDSM dataset. We have achieved the AUC = 0.85 for Faster R-CNN. The system is able to detect 90 percent of the malignant lesions with very less false positive marks per image. Since the results are more accurate, we can employ this technique for breast cancer detection which could help radiologists more cancers.

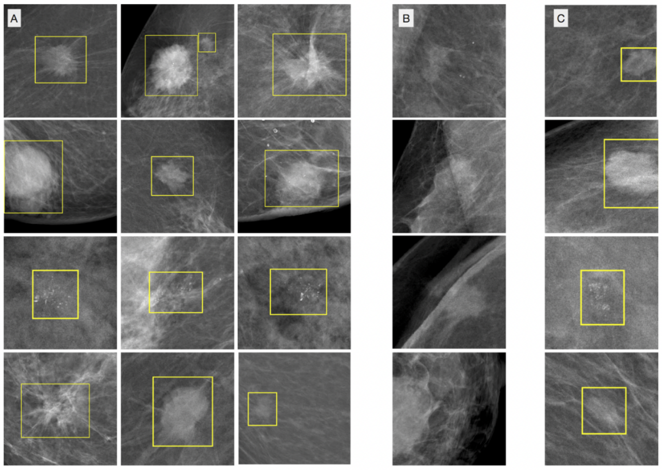

Fig. 6. Detected Cancerous mass depicted by bounding boxes. A)Correctly detected malignant lesions B)Missed malignant lesions C)False positive detections.

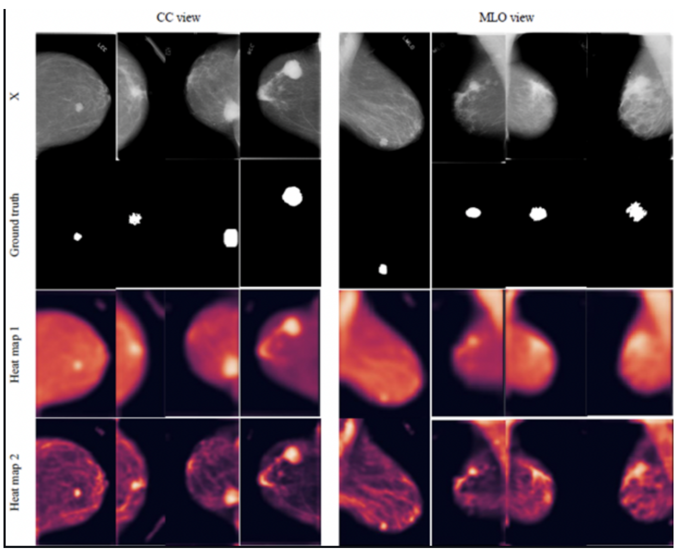

Fig. 7. Heat-maps of the left and right mammograms of breasts.

IV. Background

A. Related Work

Classification is one of the most important and essential tasks in machine learning and data mining. About a lot of research has been conducted to apply data mining and machine learning on different medical datasets to classify Breast Cancer. Many of them show good classification accuracy [22]. There are many deep learning and machine learning techniques available for breast cancer detection and prediction. Some of most used deep learning techniques for breast cancer detection are Convolutional Neural Network, Recurrent Neural Network and some pre-trained model Alex Net, Google Net, VGG16, VGG19, ResNet. Some most used datasets available for training and testing are Mammogram image, SEER, UCI, WBCD [2]. The author Abdullah-Al Nahid developed Deep Learning Model utilizing a restricted Boltzmann machine that mainly used back propagation algorithm for classify histography images [23]. Vikas Chaurasia and Saurabh Pal compared the performance of supervised learning classifiers such as Naïve Bayes, SVM-RBF kernel, RBF neural networks, decision trees to find the best classifier in breast cancer datasets [24]. A few investigations are led on clinical informational collections utilizing different classifiers and element determination strategies. Quite a bit of the examination on breast cancer related datasets can be obtained on the internet. Majority of the datasets show great order of accuracy [25]. Sivaprakasam et al. [26] compared the performance of C4.5, Naïve Bayes, Support Vector Machine and K- Nearest Neighbor (KNN) to find the best classifier and SVM turns out to be the most accurate with an accuracy of 96.99 percent. In machine learning the feature selection is the process of choosing a subset of relevant attributes from various candidate subsets, and it is a fundamental to build a training model. Feature selection plays a vital role in creating an effective predictive model. There are several benefits on applying the feature selection methods and some of the benefits are they provide more effectiveness in training the machine learning algorithm, and they reduce the complexity of a model and makes it easier to interpret, improve the accuracy of a model if the right dataset is chosen [27].

B. Overview

Breast cancer is a devastating disease, with high mortality rates around the world.[28] Breast cancer is the second most diagnosed cancer in women, affecting one in every eight women in the U.S. The goal of screening exams for early breast cancer detection is to identify breast abnormalities as early as possible. If breast cancer is found early, there are more treatment options and a better chance for survival. Women whose breast cancer is detected at an early stage have a 93 percent or higher survival rate in the first five years.[32] Screening mammography is estimated to decrease breast cancer mortality by 20 to 40 percent.[28] Mammograms are currently the best screening tool to detect breast cancer early but reading and interpreting them is a visually challenging task, error prone for even experienced radiologists," said Dr. Vijayaraghavan, associate professor of radiology, who co-authored the retrospective study with lead author Bill Lotter, PhD, chief technology officer and co-founder of DeepHealth. "We want to improve the health of women in Massachusetts with reliable tools that assist clinicians."[32]]However, there are such limitations to these screenings. To address these limitations, researchers have explored using deep learning in mammography. [28] Researchers have come up with various deep learning techniques to overcome these limitations in mammography. But they still struggle with obtaining large amounts of annotated data for training these deep learning models. [28] Cancer has become the most concern point in biomedical informatics. Breast cancers are the second highest recorded cancers from the 14 different types. There are different techniques and algorithms which are used for the prediction of breast cancer. Handcrafted feature extraction

[29] (Humoment, haralick textures and color Histogram) techniques are used for the extraction of the characteristics like texture, shape, and color of the histopathological images [29]. In this Classification we compare the deep neural network with BC histopathology images for the better accuracy results. To predict breast cancer, support vector machines (SVMs) with an attribute extraction method were presented in Akay (2009) with 99.51 percent prediction accuracy. Abdel-Zaher and Edlib (2016) presented a two-phase scheme for breast cancer classification using Wisconsin Breast Cancer dataset [29]. Data augmentation methods are used for cropping, flipping for extraction of histopathological images [29]. The main issue is the over fitting. we can also predict the breast cancer by using computer aided diagnosis which learns the nature of cancer tissues through deep brief network algorithms. In this we get these results from the Mammograms and screening, and we are going to compare with the algorithms and other techniques. In this Mass ROI'S and Whole Mass ROI'S techniques [30] to detect the mass of the effected cancer tissue. The chosen characteristics are utilized to train and evaluate standard classifiers like Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), [10] and Neural Network (NN). On the contrary, the suggested DBN-based CAD system offers extensive capabilities [30]. In Technique A (Mass ROIs), we gathered 600 ROIs and used 300 in training and 300 in testing. ROIs were distributed evenly according to class type in both training and testing. In Technique B, we gather 168 ROIs (i.e. Whole Mass ROIs) and use half of them in training and the other half in testing [30]. These techniques are used for overall accuracy, specificity, and sensitivity for the mass of the breast cancer tissues. We also used the globally aware multiple instance classifier (GMIC) [31]. Here we used the retrieve-roi algorithm to utilize the localization information from saliency maps. The other algorithm greedily [31] selects information patches of input images. We reported the test performance of the top-5 GMIC heatmap models that achieved the highest validation [31] AUC on identifying breasts with malignant lesions. The top-5 GMIC ResNet-18-heatmap models achieved a mean AUC of 0.927 ± 0.04 / 0.792 ± 0.008 in identifying breasts with malignant/benign lesions, outperforming the vanilla GMIC models (0.913 ± 0.007 / 0.791 ± 0.005). The ensemble of the top-5 GMIC- ResNet18-heatmap models [31] achieved an AUC of 0.931/0.80 in identifying breasts with malignant/benign lesions matching the performance of vanilla GMIC models (0.930/0.80)

C. Convolutional Neural network for Deep-learning

To perform classification or segmentation on large complex images, a common strategy involves the use of a classifier in sliding window fashion to recognize local patches on an image to generate a grid of probabilistic outputs [34]. After, the segmentation and classification are done we perform a set of process on the results that we obtained from them. Such methods have been used to detect metastatic breast cancer using whole slide images of sentinel lymph node biopsies [35]and to segment neuronal membranes in microscopic images [36]. The drawback of the above approach is that requires a series of steps which involves being executed distinctly. Hence, we propose a method to combine the two steps into a single step for training on the whole images [33]. Since, we will be using two data sets, on the first dataset we will use whole image classifiers and develop patches. Then we will train the classifier using two steps. The first step was to train a patch classifier where we e compare the networks with pre-trained weights using the ImageNet database to those with randomly initialized weights. The second step was to train a whole image classifier converted from the patch classifier. [34] Using max pooling and two FC layers we can test the model. The next thing would be to use a heatmap for all the convolutional networks. For the next dataset we will use transfer learning approach and check its efficiency and effectiveness

Acknowledgment

References

[1] https://www.breastcancer.org/facts-statistics

[2] N. Khuriwal and N. Mishra, "Breast Cancer Diagnosis Using Deep Learning Algorithm," 2018 International Conference on Advances in Computing, Communication Control and Networking (ICACCCN), 2018, pp. 98-103, doi: 10.1109/ICACCCN.2018.8748777.

[3] Keen JD, Keen JM, Keen JE. Utilization of Computer-Aided Detection for Digital Screening Mammography in the United States, 2008 to 2016. J Am Coll Radiol. 2018 Dec;15(1 Pt A):44–48. doi: 10.1016/j.jacr.2017.08.033. [PubMed] [CrossRef] [Google Scholar] [Ref list]

[4] Paquerault S, Hardy PT, Wersto N, Chen J, Smith RC. Investigation of optimal use of computer-aided detection systems: the role of the "machine" in decision making process. Acad Radiol. 2010 Sep;17(9):1112–21. doi: 10.1016/j.acra.2010.04.010. [PubMed] [CrossRef] [Google Scholar] [Ref list]

[5] Christoyianni, I., Koutras, A., Dermatas, E. Kokkinakis, G. Computer aided diagnosis of breast cancer in digitized mammograms. Comput. medical imaging graphics 26, 309–319 (2002).

[6] Hologic. Understanding ImageCheckerR CAD 10.0 User Guide – MAN-03682 Rev 002 (2017).

[7] Ribli, D., Horváth, A., Unger, Z. et al. Detecting and classifying lesions in mammograms with Deep Learning. Sci Rep 8, 4165 (2018). https://doi.org/10.1038/s41598-018-22437-z

[8] Gilbert, F. J. et al. Single reading with computer-aided detection for screening mammography. New England Journal of Medicine 359, 1675–1684 (2008).

[9] Kooi, T. et al. Large scale deep learning for computer aided detection of mammographic lesions. Med. image analysis 35, 303–312 (2017).

[10] Becker, A. S. et al. Deep learning in mammography: Diagnostic accuracy of a multipurpose image analysis software in the detection of breast cancer. Investig. Radiol. (2017).

[11] Dhungel, N., Carneiro, G. Bradley, A. P. Fully automated classification of mammograms using deep residual neural networks. In Biomedical Imaging (ISBI 2017), 2017 IEEE 14th International Symposium on, 310–314 (IEEE, 2017) .

[12] Lotter, W., Sorensen, G. Cox, D. A multi-scale cnn and curriculum learning strategy for mammogram classification. In Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support, 169–177 (Springer, 2017).

[13] https://en.wikipedia.org/wiki/Mammography

[14] https://en.wikipedia.org/wiki/Breast$_{i}maging$

[15] https://www.cancer.gov/types/breast/mammograms-fact-sheet

[16] Lehman, C. D. et al. Diagnostic accuracy of digital screening mammography with and without computer-aided detection. JAMA internal medicine 175, 1828–1837 (2015).

[17] Fenton, J. J. et al. Influence of computer-aided detection on performance of screening mammography. New England Journal of Medicine 356, 1399–1409 (2007).

[18] Fenton, J. J. et al. Effectiveness of computer-aided detection in community mammography practice. Journal of the National Cancer institute 103, 1152–1161 (2011).

[19] ttps://www.mathworks.com/help/vision/ug/getting-started-with-r-cnn-fast-r-cnn-and-faster-r-cnn.htmlmw$_{2}5d18973 - df6c - 48ef - aaa9 - 31a4ec9e6705$

[20] Du, Lixuan Zhang, Rongyu Wang, Xiaotian. (2020). Overview of two-stage object detection algorithms. Journal of Physics: Conference Series. 1544. 012033. 10.1088/1742-6596/1544/1/012033.

[21] b21 Simonyan, K. Zisserman, A. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556 (2014).

[22] b22 https://www.sciencedirect.com/science/article/pii/S2667305322000072

[23] b23 Abdullah-Al Nahid, Aaron Mikaelian and Yinan Kong, Histopathological breast-image classification with restricted Boltzmann machine along with backpropagation, Biomedical Research Volume 29, Issue 10, (2018).

[24] b24 V. Chaurasia and S. Pal, “Data Mining Techniques: To Predict and Resolve Breast Cancer Survivability,” vol. 3, no. 1, pp. 10– 22, 2014.

[25] b25 Y. Khourdifi and M. Bahaj, ”Applying Best Machine Learning Algorithms for Breast Cancer Prediction and Classification,” 2018 International Conference on Electronics, Control, Optimization and Computer Science (ICECOCS), 2018, pp. 1-5, doi: 10.1109/ICECOCS.2018.8610632.

[26] b26 Y. Christobel, A., Sivaprakasam, “An empirical comparison of data mining classification methods,” Int. J. Comput. Inf. Syst., vol. 3, no. 2, pp. 24–28, 2011.

[27] b27 Dhahri, Habib; Al Maghayreh, Eslam; Mahmood, Awais; Elkilani, Wail; Faisal Nagi, Mohammed (2019). Automated Breast Cancer Diagnosis Based on Machine Learning Algorithms. Journal of Healthcare Engineering, 2019(), 1–11. doi:10.1155/2019/4253641

[28] b28 Deep Learning May Detect Breast Cancer Earlier than Radiologists URL: https://healthitanalytics.com/news/deep-learning-may-detect-breast-cancer-earlier-than-radiologists

[29] b29 https://www.sciencedirect.com/science/article/pii/S2667305322000072

[30] b30 https://www.researchgate.net/publication/305703509$_{A}utomatic_{C}omputer-Aided_{D}iagnosis_{o}f_{B}reast_{C}ancer_{i}n_{D}igital_{M}ammograms_{v}ia_{D}eep_{B}elief_{N}etwork$

[31] b31 https://deepai.org/publication/an-interpretable-classifier-for-high-resolution-breast-cancer- screening-images-utilizing-weakly-supervised-localization

[32] b32 EARLY DETECTION IS KEY Url: https://www.carolmilgardbreastcenter.org/early-detection

[33] b33 Mammography expert finds deep-learning artificial intelligence may improve cancer detection URL: Mammography expert finds deep-learning artificial intelligence may improve cancer detection.

[34] b34 Shen, L., Margolies, L.R., Rothstein, J.H. et al. Deep Learning to Improve Breast Cancer Detection on Screening Mammography. Sci Rep 9, 12495 (2019). https://doi.org/10.1038/s41598-019-48995-4.

[35] b35 Dayong Wang et al. “Deep Learning for Identifying Metastatic Breast Cancer”. In: (June 18, 2016). arXiv: 1606.05718 [cs, q-bio]. URL: http://arxiv.org/abs/1606.05718 .

[36] b36 Dan Ciresan et al. “Deep Neural Networks Segment Neuronal Membranes in Electron Mi- croscopy Images”. In: Advances in Neural Information Processing Systems 25. Ed. by F. Pereira et al. Curran Associates, Inc., 2012, pp. 2843–2851. URL: http://papers.nips. cc / paper / 4741 - deep - neural - networks - segment - neuronal - membranes - in - electron-microscopy-images.pdf