A Review of Computer Aided Diagnosis Model Stage for Mammogram Classification Model

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Abstract
Many CAD systems have been developed by various authors using machines or deep learning methods. The goal of such systems is to identify the patients with COVID-19 positive. Most of the existing CAD systems are based on standard steps i.e. pre-processing in which the acquired images are enhanced to get the clear images before providing the input to the CAD system. Segmentation is used to detect disease part or the ROI is segmented from the image. There are many methods used for feature extraction like Otsu thresholding that can extract features from image and identify the area to segment. Finally learning Methods are used to classify images into positive or negative category. In this paper the goal be to explore best learning method to train the system for cancer detection.
Keywords: DNN, Mammogram, LEARNING, X-RAY, CAD

1. Introduction

The Cancer is a large group of related illnesses caused by the unrestrained division of body cells which spread, crowd out normal cells, and develop into a tumor that is benign or malignant [1][2]. Benign tumors develop slowly and do not attack neighboring tissues or extend to other parts of the body; therefore, they are cancerous. However, malignant tumors are cancerous and since with time they spread to neighboring tissues such as the lymph nodes which can cause the failure of major organs. Cancer can begin anywhere in the human body; therefore, the name of cancer depends on the affected area. Among cancer types, breast cancer is a top killer for women [3]. Although breast cancer can also develop in men, however, the highest risk and incidence is in women above 50 years. Breast cancer occurs because of the abnormal development of breast cells where the cells divide faster than healthy cells, accumulate, and form a mass. This cancer can either begin within the lobules glands which produce milk, or the milk ducts, which are used to transport milk to the nipple. Though unlikely, breast cancer can begin within the stromal tissues, that embody the fatty and fibrous connective tissues of the breast[4]. Breast cancer is the second most common killer for women, [5]. In [6] author reported about 2,088,849 (11.6%) new breast cancer cases and 626,679 (6.6%) breast cancer deaths in [11]. The survival rates of breast cancer patients vary in the world because it depends on factors such as age, geographical factors, and race, however, a relative survival estimate is 91% at 5 years diagnosis, 86% after 10 years, and 80% after 15 years [12]. A report by International Agency for Research on Cancer (IARC) showed that there are more deaths in less developed regions than the developed regions because a shift in lifestyle is causing an increase in incidence, and also because clinical advances to combat the disease are expensive and sometimes unavailable. Because of several contributing factors, there has been a general increase in breast cancer cases in recent years. A study conducted in 2017 on cancer incidences from 2005 to 2015 showed an increase in

breast cancer cases by 33%. Out of which 12.6% of the incidences were because of population growth, 16.4% because of an aging population, and 4.1% was because of increasing age- specific incident rates [13]. According to the Globocan report of 2018, breast cancer caused 74072 deaths and 168690 incidences in Africa.

2. COVID-19 Detection Methods

1. Image Acquisition: In this step a benchmark or clinical dataset will be acquired as input for proposed CAD based system.
2. Image Pre-Processing: The quality of images will be enhanced using various noise removal methods.
3. Image- Segmentation: The image segmentation is done to segment the disease from image instead of focusing on complete image.
4. Learning Networking Training and Testing: A deep neural network learning based method will be used for network training and testing.
5. Classification of the Images: Classification of images into micro, masses and normal calcification by proposed learning model.
6. Category Detection: Detection of cancer classification for single image or real time image which was not available in dataset.

The proposed model will show better accuracy and better outcomes for other parameters with less complexity.

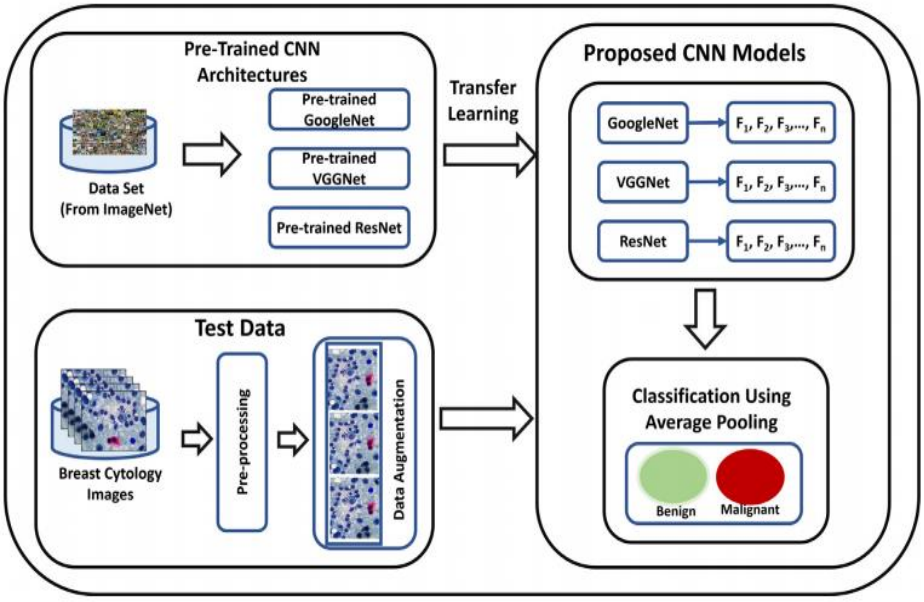

Fig. 1. Block Diagram of the Proposed Deep Learning Framework.

In this paper, author proposed a transfer learning based model for system training and testing. The classification of the images done as benign and malignant.

3. Literature Review

(Hamidinekoo et al. 2018) author had provided an overview of various recent techniques and methods used in mammography based on deep learning. A variety of techniques and datasets along with methods are reviewed by the author. Most of the present models are based on deep neural network learning with variety of learning methods like CNN, DNN and RNN. The author conclude that most of the existing methods are based on common steps where pre-processing is one of the major step to improve the original image in dataset. There are variety of methods and techniques used by many authors for pre-processing and image enhancement. Then based on any deep learning the network is trained and tested over the images in dataset and finally based on testing and training system is able to predict or detect the abnormalities in the breast image to classify it in micro or macro calcification. Many existing techniques reviewed by author had shown accuracy up to 85%.

(Ragab et al. 2019) had proposed a method to detect breast cancer based on CNN and SVM. Author used CAD system for image segmentation in which initially goal is to segment the ROI of image. The CNN method is used extract features from images, for this purposed author had used Alexnet which is pre-trained model and the last layer of the model is further connected to SVM. DDSM dataset is used in paper and to obtain better accuracy training is done using large data samples. The proposed method used in paper achieved around the accuracy of 77% with usage of deep convolution network.

(Loizidou et al. 2020) had proposed a temporal operations based automated detection of micro calcification in breast. In this work the machine learning is combined with temporal subtraction to enhance the accuracy and detection rate. The proposed work is simply based on images operations, where the original and outcome images are compared and further with the help of support vector machine the images are classified in to micro or mass calcification.

(Suhail, Denton, and Zwiggelaar 2018) had done the classification of various mammogram images using a discriminant fisher method. The goal of paper is to classify the inputted image in to benign or malignant. The proposed method encode the images to a binary value. Linear classification method is used along with support vector machine to classify the images in both categories and author achieved and accuracy of around 96%.

(Bakalo, Goldberger, and Ben-Ari 2019) had used a deep dual bunch technique for detection of abnormalities in medical images. The proposed method is based on two learning branches, where the first learning branch is used for regional calcification and other branch is used for detection. The effect of classification and localization considering the factor of cost is monitored. The method is tested on a dataset of 543 images with accuracy of 76%. Further major scope of improvement is suggested by author to include the phase of learning.

(Ouyang et al. 2019) had worked on various H-SCAN ultrasound images of breast to classify them in three categories of benign, malignant and normal. Working on images the finding of author was that in case of more red color distribution the chance of cancer are high and where in case of blue color the image are classified as normal category images. The RGB spectrum

had shown a major difference in between benign and malignant image on basis of their broadcast color.

(Sharma and Mehra 2020) had used combination of two machine learning methods to classify a mammogram image. Initially during preprocessing the region of interest was identified and images were pre-processed using Hue lumen method. Then the network is trained to detect any image as macro calcification with the help of CAD system only.

(Huan and Wen 2020) had done face classification with the help of dual learning model which is based on DNN and transfer learning. The used modes was used to train a network of around 169 layers. The basic classifier used by author had shown the accuracy of 65%. Transfer learning provides the easiest way to share and understand data.

(Sannasi Chakravarthy and Rajaguru 2019) had worked on noise removal process from image, and major goal of author is to eliminate impulse noise. Initially the corrupted or noisy pixels are detected and a healing algorithm start to correct the pixels. The pixels that are easily identified with impulse noise are classified under bidirectional decomposing pixels. The proposed method is compared with various existing methods on basis of peak signal to noise ratio (PSNR) and PSNR value for proposed method is higher than existing methods.

(Palee et al. 2019) had proposed a heuristic approach based on DNN learning methods to detect hydatid form mole. The study is done on 17 different critical features to differentiate between PHM and VHM. The characteristic for train the networks are defined a system extract features out of that to provide neural network data to learn and to classify. Author further suggested to include more images of cell to explored structure in better way. (Agarwal et al. 2020) had developed a method using deep learning for mass detection in mammogram image. Proposed framework is fully automated for mass detection and used the concept of transfer learning. Overall, 78% accuracy is derived by author in this paper.

(Bruno et al. 2020) had proposed a novel solution based on SIFT algorithm and deep learning for spacious regions detection in mammogram image. Proposed method outperform quite well in contrast with other techniques. Author also state that the lack of dataset availability data is also one of the factor which decreases the accuracy. So, the need is to train network using bigger datasets to train and test system properly.

(Chowdhary and Mittal 2020) had proposed an efficient method for segmentation and classification of mammogram images using k-mean and SVM learning method. The author used the technique of machine learning to classify the images in to various categories. Initially during pre-processing various operations are performed to enhance the PSNR of the image for better classification.

(Gupta and Tiwari 2017) had used a tool based method for image enhancement and for better segmentation of micro and mass calcification. Author proposed a histogram based method which helps in enhancing the PSNR value of inputted image and helps a radiologist to see image clearly. Also the segmentation method can segment mass calcification areas from original image. The average PSNR value obtained by author proposed method was around

18.90 using CLAHE Median method which is enhance PSNR in contrast with other existing methods (Refer Table 2: (Gupta and Tiwari 2017)).

(Liu et al. 2020) had proposed a CAD based technique for cancer segmentation from an image. The proposed method is implemented in MATLAB 2017 using MIAS dataset. The noise removal method is used along with segmentation bit wise, the PSNR value of final image is higher than the existing methods. The final image had shown sharp edges which make the image quite clear and easy to study.

Contrast enhancement helps in enhancing the mammogram images for better cancer detection (Shelda Mohan 2013). The author proposed an enhancement method based on CLAHE and LCM for mammogram image contrast improvement. The used method is quite adaptive in terms of pixel distribution and replacement during the preprocessing stages. The work done had shown a significant improvement in the mammogram images in terms of PSNR (Peak Signal to Noise Ration).

Automated breast ultrasound can be an adjacent technique for mammography to detect breast cancer during early stages (Hashem et al. 2020). The author compared three major used clinical techniques for breast cancer detection. Tomo-synthesis and ABU can provide a close accuracy for cancer detection in contrast with existing mammogram based methods. The study was performed to evaluate the accuracy and consistency of 3-D imagining for breast cancer detection.

Table I Accuracy of Various Exiting Architecture

Method	**Architecture**	**Accuracy**
(Guan and Loew 2017)	VGG-16	96%
(Lopes and Valiati 2017)	CNN and SVM	90%
(Shen et al. 2019)	RESNET	92%
(Shen et al. 2019)	VGG-RESNET	89%
(Trivizakis and Ioannidis 2019)	Dense-NET	78%
(Alzubaidi and Al-Shamma 2020)	Transfer Learning	96.10%
(Falconí and Pérez 2019)	RESNET-50	79%
(Falconí and Pérez 2019)	Mobile-NET	75%
(Kassani, Wesolowski, and Schneider 2018)	Transfer Learning Based Method	92.50%
(Jiang and Liu 2017)	Google-NET	88%
(Yousef et al. 2019)	CNN-NET	87.50%

Conclusion

Effective screening of mammogram cancer can extend the survival rate for women. Mammography is the recommended imaging test for breast cancer identification because it can recognize breast cancer cells many years in advance before physical indicators appear. However, many suspicious findings on a mammogram are benign tumors that eventually require a patient to undergo unnecessary biopsies, consequently causing anxiety to patients and increase the cost of diagnosis. Further, the transfer learning is the future to accurately detect breast cancer.

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