A Study on Convolution Neural Network for Breast Cancer Detection

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Abstract— Mammography is a widely used imaging technology for the detection and diagnosis of breast cancer. A computer-aided automatic classifier with the help of machine learning can improve the diagnosis system in terms of accuracy and time consumption. These types of system can automatically distinguish a benign and malignant pattern in a mammogram. Deep learning algorithms have gained a lot of popularity in recent years. Convolution Neural Network has become a preferred choice for images analysis including a mammogram. In this paper, we review various deep learning concepts applied to breast mammogram analysis and summarizes contributions to this field. We present a summary of the recent developments and a discussion about the best practices done using CNN in mammogram analysis and improvements that can be done in future research.

Keywords— Mammogram, CNN, RCNN, Deep Learning, YOLO, Mass, Benign and Malignant, Microcalcifications

I. INTRODUCTION

Breast cancer occurs when the cells in bosom tissue mutate, keep reproducing. These mutated cells group together to form a tumor. A tumor is said to be cancerous or malignant when they spread to other parts of the breast and successively, through the lymph system and bloodstream, to other body parts. It may start from the lobules in the mammary glands or lactiferous ducts that carry milk to the nipple from the lobules. There are also other types of less common breast cancer such as the one that originated from the fatty and fibrous connective tissue inside a breast. Breast cancer occurs when a genetic mutation takes place in the DNA of the cell inside a breast. The reason why and how this mutation occurs is not entirely known [1].

After lung cancer, breast cancer is the main cause of mortality in women. It is also the most prevalent type cancer among women[2]. Early detection is very important because if the disease progresses, treatment is difficult and in some case lead to mastectomy or may be fatal. Mammography for breast screening is the most effective tool for this purpose. Mammogram utilizes a low energy x-ray to take the picture of the breast[3]. Breast mammography can help in the detection and analysis of different breast abnormalities such as mass, calcification and architectural distortion. These abnormalities can estimate breast cancer development risk in patients. In the traditional clinical setting, this analysis process is manually done by a radiologist. This process depends on the skill and expertise of the radiologist and can result in huge variability in the final estimation [4]. As a result of this possible impact, there is a rise in many researchers working in developing such a computer-aided diagnosis system. A computer-aided diagnosis system for breast cancer detection in mammogram will extract features from the images and will used these features for classifying normal and malignant breast. Such a system will provide a second opinion to the radiologist about the presence of cancer in a mammogram. The feature extraction process can be manual or automatic. Mammogram with breast cancer have different features because of the presence of masses, microcalcification or architectural distortion. These features will be used for training a neural network for classification.

Handcrafted features depend on the method chosen for the extraction process. A sensible step towards this challenge is automatically learn the features according to the problem. This is the main idea behind various deep-learning algorithms. Convolutional neural networks (CNNs) has become the most successful type of models for medical image analysis. CNNs was first introduced in the late seventies [5]. In 1995, Application of CNNs to medical image analysis was done for the first time [6]. The first successful real-world application for hand-written digit recognition using CNN [7]. A turning point in this field was came during the ImageNet challenge [8]. A proposed CNN architecture, called AlexNet, has a large impact on the field of deep-learning by winning that competition with a wide margin. Further progress has been made using deeper architectures in subsequent years that performs much better than AlexNet [9]. An overview of various hand techniques for a system using handcrafted feature is presents [10].

Research articles on deep learning in medical image analysis has grown rapidly since 2015 and is now a dominant topic in many conferences. There are also competitions that were held recently to attract researchers and developed new method for improving mammogram classification for breast cancer detection (i.e. DREAM).

Our survey mainly focuses on the application of convolution neural network in mammogram image analysis. Traditional approaches using handcrafted features are excluded. Recently, interest has returned in the topic and gained significant advance. The rest of this paper is organized as: Section 2 discusses various abnormalities that can affect breast and their characteristics. Section 3, discuss briefly convolution neural network and its variations that have been used for mammogram image analysis. Section 4 describes various publicly available databases. Section 5 describes various contributions of deep learning in breast mammogram analysis followed by a discussion,conclusion and future works.

II. BREAST ABNORMALITIES

Breast abnormalities that can affect breast tissues can be broadly classified into three categories:

A. Masses/Lumps

Sometimes localized swelling, bulge, protuberance or bump develops in the breast. These parts are different from

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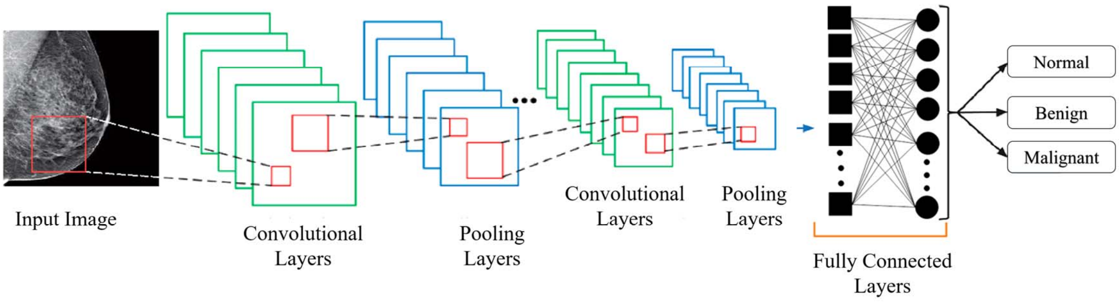

Figure 1: Typical CNN architecture

the breast tissue around it or in the same area of the other breast. These swelling are called mass. They are characterized by their shape, contour, and density Breast masses can be benign (not cancerous) or malignant (cancerous) [11, 12].

B. *Microcalcifications*

Breast microcalcifications occur when there are small calcium deposits in the tissues of the breast. They are divided into benign, suspicious or high probability of malignancy. Benign calcifications tend to be larger and have an appearance much different from the surrounding tissues. They do not require magnification to study. While the suspicious ones smaller and magnification is required to study its characteristics [13].

C. *Architectural distortions*

In architecture distortion, the normal architecture of the breast is distorted without any associated mass. Such distortion may look like abnormal tissues arrangement radiating from a point, focal retraction or somewhat random pattern. These types of distortion can be the clear center (central opacity) or dense Centre.

Apart from the one mention above, intra-mammary lymph node, asymmetric tubular structure, overall asymmetry of the breast tissue and the asymmetric focal density are some of the other abnormalities [14].

III. Convolution Neural Network.

Convolution neural network (CNN) is similar to Multilayer perceptron (MLP) in the sense that both are made up of neurons which have biases and learnable weights. When the neurons receive some input, it will perform dot product. In, CNNs the network share the weights in such a way that convolution is performed on the images. A CNN having mainly three layers stacked one over the other as shown in Figure 1. At the beginning of the network, low level features are extracted. As we progress through the network, higher level features are learned[15,16]. The function of each layer is as:

Convolution Layer: Comprises a set of independent filters that are convolved independently within the image and resulting in feature maps for each of the filters.

Subsampling/Pooling Layer: Purpose of this layer is to progressively reduce the spatial size of the representation so that the number of calculation is reduced Pooling layer operates independently on each feature map.

Fully Connected Layer: Connected at the end of CNN after several convolutional and max pooling layer. Here, all the neurons are connected to all activations in the previous layer. The high-level reasoning is performed by this layer. Using a matrix multiplication followed by a bias offset, the activations can be calculated.

A. *Region based Convolution Neural Network (RCNN)*

R-CNN is a specific way of applying CNN for the task of image segmentation. The main objective of RCNN is to take an image as input and outputs bounding boxes and labels for each object in the image. This process can be divided into two components, the region proposal, and the classification. In region proposal step, RCNN creates bounding boxes using Selective Search. Selective Search, using windows of varying size, look at the image and tries to group neighboring pixels by texture, color, or intensity. After the bounding boxes are created, the regions are wrap to a standard square size. It is then passed through a modified version of AlexNet. At the end of the network, an SVM is added to classify.

B. *Fast RCNN*

Fast RCNN was developed to solve some problems of RCNN and build a faster objection detection algorithm. The approach of Fast RCNN is same as RCNN, but instead of feeding the region proposals to the CNN, the input image is used as input to a CNN to generate a convolutional feature map. Using this feature, the region of proposals is identified and is wrapped into squares by using an ROI pooling layer. A softmax layer is used at the end of the network to predict the class of the proposed region and also the offset values for the bounding box. In Fast R-CNN the convolution operation is done only once for each image, and from it, a feature map is generated.

C. *Faster RCNN*

Both R-CNN and Fast R-CNN uses selective search to find the regional proposals which are slow and time consuming. Faster R-CNN was developed to eliminate the selective search algorithm and let the network learn the region proposals. In Faster RCNN, the image is provided as an input to a CNN which outputs a convolutional feature map. But instead of using a selective search, a network is used to predict the regional proposal. Then, using an ROI pooling layer, the predicted region proposals are reshaped. This will be used to classify the images within the proposed region and predicts the offset value. This algorithm was able to provide a much faster execution than its predecessors.

D. *YOLO*

In YOLO, a single convolution neural network is used for the full image. This network will divides the image into many regions and try to predict bounding boxes. The probabilities of each region are then calculated. These predicted probabilities will be used for weighting the bounding boxes. It is much faster than RCNN, Fast RCNN and Faster RCNN. Disadvantage of YOLO is that it is difficult to detect small objects.

E. Advancement in hardware and software

GPUs are becoming more affordable. There are also various GPU computing libraries, such as CUDA, OpenCL etc. which are easily available. This lead to a steep rise in the use of deep learning in different fields. Another reason for the wide availability of open source software packages. Some of the most popular packages are: Caffe [17], PyTorch [18], Tensorflow [19], Theano [20] and Torch [21].

IV. MAMMOGRAM DATASETS

A large data set is necessary for applying deep learning. In many of the paper on the mammogram, small datasets are used that results in variation in performance. Many projects try to solve this problem by using techniques such as semi-supervised learning [22], transfer learning [23, 24, 57] and weakly supervised learning [25]. Some technique to improve the shortcoming of fewer data can be seen in [28, 26, 27]. [29] shows that good performance can be achieved by using a large dataset. Some of the publicly available databases of the mammogram and their descriptions are as follows:

- MIAS Mini Mammographic Database (mini-MIAS)

Mammographic films are collected from UK National Breast Screening Programme. This database consists of 322 digitized films. The database also provides a ground truth about the abnormalities if present in an image [30].

- Digital Database for Screening Mammography (DDSM)

This database contains 2,620 scanned film mammographic studies. For images containing suspicious areas, pixel-level "ground truth" detail about the locations and types of abnormalities are provided [31]. There are also some curated and standardized versions of DDSM. Curated Breast Imaging Subset of DDSM (CBIS-DDSM) is a curated version of the DDSM [32].

- Mammographic Image Database for Automated Analysis (MIDAS)

All the images are in DICOM format, and they are collected from at Janice Lamas Radiology Clinic. This database consists of about 600 digital mammograms. Each mammogram consists of two images for each breast, patent information, abnormality descriptions, breast composition, BIRAD categories, and overall impression. [33].

- Breast Cancer Digital Repository (BCDR)

This repository consists of mammogram and ultrasound images of 1734 cases. It also provides medical history of the patient and mask of the segmented abnormality region. The cases are annotated by expert radiologist [34].

V. DEEP LEARNING IN MAMMOGRAM ANALYSIS

A. Steps in breast cancer detection

The CAD system is a combination of various image processing techniques. The first step is preprocessing in which artifacts and labels are getting removed. Noise is also removed in this step using a filtering technique. The second step is enhancement which allows enhancing contrast and edges in mammogram image. Next step is to divide an image into its constituent parts called as segmentation. The feature of the region of interest (ROI) is then calculated. The final step is to classify the data into a normal, benign or malignant image. Each step in a mammogram CAD system is shown in Figure 2.

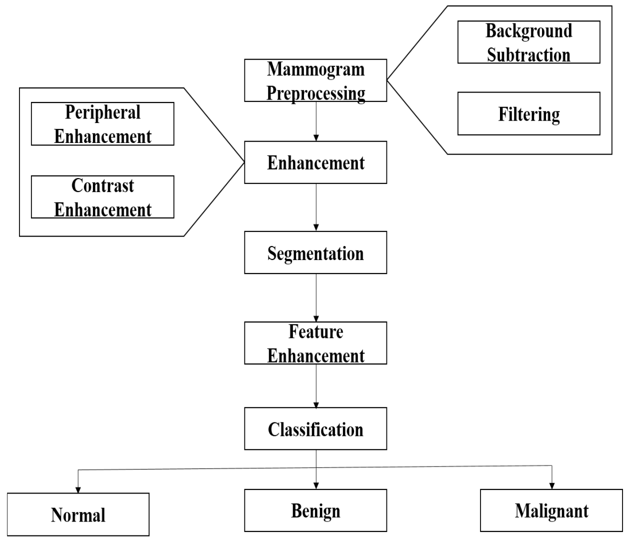

Figure 2: Basic steps in CAD System for the breast abnormality

B. Mass Analysis

The first use of deep learning in mammogram analysis reported in [37]. This paper investigates the performance of various CNN architecture and texture features on mammogram analysis. Implementing of such a network was considered to be computationally expensive and time consuming. However, due to the development of the parallelizable algorithm and powerful GPUs in recent years, application of CNN in mammogram analysis become more feasible. In [35], a system for breast density classification using a generic multi-scale DAE that used a sparsifying activation function was proposed. The result was compared with manual BIRADS and Cumulus-like density scoring [36]. It shows that multiple scales could effectively learn good features in the segmentation task. As an improvement to this work, a CSAE network with scarcity regularization was proposed in [38].

The use of ADNs [40], an unsupervised and hierarchical model, in mammogram analysis was first explored in [39]. It uses a sparse convolution coding and max pooling. The feature map is combined with an SPM kernel [41], and an SVM is used for the classification.

Performance of various deep CNN architectures in mammogram analysis were tested by [42, 43]. From their research, they were able to get two models which give the best performance, a model using HOG and HGD and another model that uses 17 hand-crafted features. They also proposed a model which used the combination of both handcrafted and CNN learned features and the proposed model showed an improvement in the performance.

In [45] used an HT-L3 CNN [44], for searching architecture best suited for mammogram analysis. In this, top 3 best architectures are selected from 729 candidates which are used for automatic feature extraction, and the features are used to train an SVM.

In [46], proposed a system that uses a combination of multi-scale 4-DBN and a GMM classifier for mass detection. Candidate mass is generated, and features are extracted from the candidate mass using CNN. The features are used for training an SVM classifier. Then, an inference is performed by using a cascade of two RF classifiers. The final result was achieved by merging the regions with high overlapping ratio.

In [26], a region-based CNN (Faster RCNN) is proposed for detection and classification of tumor. In this model, the entire mammogram was divided into many overlapping regions and a RCNN is used detecting and classifying the tumor. [59, 60] also used another region-based CNN, known as You Only Look Once (YOLO), for automatic detection and classification of masses in mammogram. A multi convolution deep layer with a confidence model was used for automatic detection and classification of masses. The masses were then classified using a fully connected layer.

In [48] proposed a model for segmenting masses and microcalcifications in a mammogram by fine-tuning a CNN, which is pre-trained with ImageNet, with unregistered mammogram. The model was able to give a better classification performance than randomly initialized CNNs. Using a pre-trained network can reduce over-fitting of the training data. Their conclusion is also supported by a work in [47]. In their paper, it was shown that a pre-trained CNN model and Random Forest classifier on features using pre-trained network could perform better than the Random forest classifier on hand-crafted features and CNN which are not pre-training.

As a solution to limited mammogram images, transfer learning is used to extract features from mammogram using pre-trained CNNs on natural images [22]. In their work, it was found out that using location, context information, and other handcrafted features can improve the performance of classification. In [50], proposed a CNN trained on LSVRC [49] was used to fine-tune mammogram images. Features are extracted using this model, and it is used for training two linear SVM. At last, the output of the two classifiers is fused to achieve the complete classification. [24] used a pretrained CNN on mammogram image to detect masses in tomosynthesis. The proposed model was able to achieve better performance and model using deep learning can outperform using handcrafted features. It can also be seen in [51] for detection of microcalcification.

[52] proposed a model for tissue classification by segmenting pectoral muscles, nipple, fibroglandular tissue, and the breast tissue. In [29], performed a comparison of the model using traditional and deep learning and concluded that model with deep learning outperforms the other. In their work, soft tissue densities were calculated from breast tomosynthesis. [23] also perform a comparison on CAD for the mammogram with handcrafted features and features extracted using CNN. They concluded that the CAD with CNN outperformed the conventional CAD. The effect of data augmentation in the performance of a model for mammogram analysis was studied in [53]. From the study, it was concluded that increasing the number of training images, using data augmentation, can improve the performance of the system.

C. Microcalcification Analysis

There are few papers related to the detection and classification of microcalcification in the mammogram. Detection and classification of calcification using thresholding is a common technique used by many models as the density calcium is very different from the other area of the breast [54]. Thresholding cannot be used for the detection of masses and other abnormalities as their density are similar to the breast tissues to some extent. For the first time, [55] used CNN for the detection of microcalcification in the mammogram. The number of images used in this model is limited, but significant increase in the performance was achieved.

A model that uses a stacked denoising AE to analyze microcalcification in the mammogram was proposed in [56]. Features are extracted using statistical and textural measurements for classification. Performance is compared with other classifiers such as SVM, K-nearest neighbor, and LDA methods. The features are directly used for the comparison of the classifiers rather than the raw data. They also concluded that deep learning-based methods give better performance as compared to other ANN based methods in classification of breast mammogram.

A method for selecting an ideal CNN architecture for classifying candidate microcalcification was proposed in [51]. This method uses grid search method for the selection process. These candidate microcalcifications are detected during pre-screening stage. A total of 216 combinations are considered using varying filters, kernel sizes, and gradient parameters. They concluded that a better classification could be achieved using the proposed model. In [57], proposed a system, based on two mammography view-level decision, for classifying benign and malignant microcalcification. The features from each of the views are then non-linearly combined and used for the decision making. Table 1 shows the comparison of various methods that are based on deep learning and their performance in mammogram analysis.

VI. Discussion,Conclusions and Future Works

A. Discussion

The aim of this survey is to provide insights for researchers, to the application of deep learning architecture in the field of breast cancer detection in mammogram.

In recent years, as seen in Section V, deep learning architectures have been widely applied in the many areas of mammogram image analysis, in areas such as abnormality detection, abnormality segmentation, and classification. Most of these applications have been tested on different network depths and varying input size to address various issues. Most of the models are reported to achieve improvement in the performance over the existing state-of-art techniques. It is also found that the performance of the majority of the methods is directly related to the correctness of the training data. But the annotation provided on the skill and expertise of the radiologist. There are no options for annotation agreement or disagreement in the available datasets. If such options are available, it helps greatly help in reducing errors.

From the literature review, it is found that the system using deep learning features outperforms those systems using handcrafted features. Some researchers were able to achieve a better performance by combining CNN based features with hand crafted features. More intelligent combination can be explored for better performance. It is also seen that the use of an SAE can also improve the performance of the system. Region-based CNN also provides faster detection and classification as a contrast to separate segmentation, feature extraction, and classification. Applications of various versions of RCNN can be seen, and among them, faster RCNN achieved better performance than its predecessors. Until the time of writing this paper, YOLO method provides the best performance.

Although some of the system provides good performances, they need a lot of computations. Some system results a decent performance with less computation. Other systems, such as the one using RCNN, are good for one problem but may not work well for a different problem. In developing such CAD, a balance of all these limitations must be taken into account.

B. Conclusion

Our study showed different applications of CNN in the field of mammogram analysis. This work summarizes the history, different model of CNN, recent advancements and the current state of art for mammogram analysis. We anticipate that this paper can provide insights for researchers, to the application of deep convolution neural network in the field of breast cancer detection and diagnosis in mammogram.

C. Future Works

The CAD systems using RCNN were performed on a small dataset. This system can be tried on large datasets to check if the accuracy of cancer detection can be improved. We can also try using newer RCNN like masked RCNN. There are also newer versions of YOLO which provides better performance on natural images and videos. These methods have not yet used for mammogram analysis. We can try this method and see if they can also improve efficiency in breast cancer detection.

From some research [61], it was proved that there are a lot of associations between mammogram and histology. Information in a histology have some relation to the occurrence of abnormalities in a mammogram. From the research, it is also known that changes in the cellular and nuclear structure can lead to change in tissues and thus can lead to the formation of microcalcification, masses, and other abnormalities. Most of the existing studies relating these two methods are done through statistical risk analysis and observations. A computer-aided system for associating these two modalities has not developed yet. Considering the biological associations between these two modalities and the development in new deep learning algorithms, a model for better cancer detection can be developed for associating these two modalities. In the future, we will try to develop a model based on deep learning that can automatically associate the mammographic and histologic information for better breast cancer detection.

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Methods	Purpose and Remark	Dataset	Results
CNN and texture feature [37]	-First application of a CNN to mammography - limited number of images --No automatic detection of ROI	-168 masses and 504 normal breast tissue	-AUC 0.87 -TP 90% - FP 31%
CNN [45]	-Feature extraction using a pre-trained network and classification using SVM for breast density estimation -Private database -Time consuming and poor performance	-1157 subjects	-Average kappa value 0.58 -Accuracy 73.05%
CNN with softmax classifier [48]	-Pre-trained network for analysis of unregistered mammogram - Whole mammographic exam is considered instead individual view which results in better classification	-INBreast and DDSM	-AUC 0.91(DDSM) -AUC 0.97(INBreast)
DBN, CNN and RF [46]	-Detecting masses in mammograms using a cascade of deep learning and random forest classifiers -No detection of suspicious areas -Added a layer for regression using hand crafted features	-DDSM-BCRP and INbreast database	-INbreast: 0.96±0.03 TPR at 1.2FPR -DDSM-BCRP: 0.75 TPR at 4.8 FPR
Faster R-CNN [26]	-Region proposal CNN (RCNN) for the detection and classification of masses -Automatic detection of suspicious regions, so no ROI dependent for testing	-850 images	-AUC 0.72, -Accuracy 0.77(BI-RADS-2{345}) - AUC 0.6, - Accuracy 0.78(BI-RADS-2{45})
Handcrafted feature and CNN [43]	-Combination of handcrafted features and CNN features for lesion classification -Provides a better classification performance than using only CNN	-BCDR database	-AUC 0.826
CNN [52]	-CNN for tissue segmentation and classification -Private images and patches	-40 images -800,000 patches	-Dice coeff. 0.71
Handcrafted feature and CNN [46]	-Combination of different handcrafted features and CNN features for mass classification -Provides a better performance using more number of images from public database	-INbreast dataset	-Accuracy 0:93 ± 0:06(CNN) 0:94 ± 0:03. (RF on CNN)
CNN [25]	-Detection and localization of masses using Weakly supervised CNN. -Provides an automatic localization but poor performance	-DDSM and MIAS dataset	-Accuracy 0.6957(Classification) -AP 0.3256(Localization)
CNN [58]	-Mass classification using a pre-trained CNN on natural image patches. -No automatic detection of suspicious regions and ROI dependent	-607 images including 219 lesions	-AUC 0.86
CNN and SAE [38]	-Breast density classification using unsupervised CNN feature learning with SAE. -Limited number of images -Gives a better performance when SAE is using along with CNN	-394 cancerous, and 1182 normal images	-AUC 0.59
CNN [28]	-Mass detection on a patch level using CNN -Small number of image patches -Gives a good performance by using the patches directly	-398 patches-199 malignant and 199 normal	- AUC 0.87
CNN [22]	-Semi-supervised CNN for classification of masses -Private images, no automatic detection of suspicious regions. ROI dependent.	-1874 pairs of mammograms	-AUC 0.8818 -Accuracy 0.8243
CNN [50]	-Combining intensity information and deep features to improve performance. -These combination gives a better performance but time consuming. -Two classifiers are used for classifying middle level and high-level features.	-DDSM	- Accuracy 96.7%
CNN [23]	-Classification of malignant and benign cyst using pre-trained CNN -Effects of data augmentation, depth, resolution, mixing, contrast features and size are discussed - Combination of CNN features with contrast features gives a better result	-1804 images	-AUC of 0:80
CNN [24]	-CAD for microcalcification detection using deep Learning - An optimal CNN architecture is selected using a grid search from a parameter space of 216 combination	-64 digital breast tomosynthesis	-AUC: 0.93
CNN [51]	-Transfer Learning from mammogram for mass detection in tomosynthesis -Significant performance improvement can be seen using transfer learning from mammogram	-train: 2,689 mass patches; -test: 183 mass patches	- AUC: 0.80
CNN [56]	- Assess the accuracies of microcalcifications and breast masses, either in isolation or combination, for classifying breast lesions - Combination of mass and microcalcification provides a better classification result	-1000 mammogram images -677 benign, 323 malignant	-Accuracy 96.24%
YOLO [60]	-YOLO based model for simultaneous detection and classification of masses -Region based CNN provides a fast and better detection and classification - Performance is not good for microcalcification or when the ROI is very small	-DDSM	-AUC 99.7 - Accuracy 97%

TABLE 1: Deep learning based methods used for mammogram analysis