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Breast Cancer Lesion Detection and Classification in Radiology Images using Deep Learning

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Abstract

Mammography is a primary diagnostic measure for early detection of breast cancers that makes the patient realize the changes much earlier than they feel the changes in their breasts. The Computer Aided Diagnosis (CAD) system uses digitized mammography images and identifies the abnormalities present in breast. Deep learning methods learn the features of the image from the limited number of expert annotated data and predict the necessary objects. The performance of convolutional neural networks (CNN) in various image analysis tasks such as image detection, recognition and classification, have excelled in recent times. This paper proposes an automatic detection and classification of breast cancer lesions in mammograms by using highly accurate and advanced object detection deep learning method Faster R-CNN. The proposed CAD system uses 330 mammography images in which 121 annotated images are used for training the Faster R-CNN network. The proposed system generated a mAP (mean Average Precision) value of 0.857 for the testing set.

Key-words: Breast Cancer, Mammogram, Faster R-CNN, Breast lesion detection, Breast lesion classification, Deep Learning Network for Faster R-CNN.

Introduction

Cancer is the critical deadly disease in the world. Especially Breast cancer is said to be the most commonly occurring cancer in women across the world [1]. In India a woman dies in every 8 minutes due to breast cancer [2]. Lack of early detection of breast cancer leads to high mortality rate.

Three important preventive steps which help for the early detection of Breast cancer are monthly breast self-exam, regular clinical breast exam and screening mammogram. The high death rate is mainly due to the lack of early detection of the cancer. Screening mammography reduces breast cancer mortality by about 20% to 35% in women aged in the range of 50-69 years. The mortality rate reduced further due to 14 years of follow-up in women aged in the range of 40-49 [3].

Mammography is a primary diagnostic measure for early detection of breast cancers that makes the patient realize the changes much earlier than they feel the changes in their breasts. A mammogram may also help to determine high risk cancer factors such as dense breasts which contain high amounts of glandular tissue. The mammographic process is reckoned to be time taking, tedious and more importantly it is subjected to errors [4]. CAD systems which were proven to be working well in accurate diagnosing of medical images, can be used in mammography to address these issues [5].

The CAD systems use Machine Learning (ML) capabilities of software systems. ML with extensive and deeper approaches i.e., Deep Learning (DL) are also being used in CAD systems for better results, due to its ability to deal with complex cases [6].

This paper proposes an automatic detection and classification of breast cancer lesions in mammograms by using highly accurate and advanced object detection deep learning method Faster R-CNN. Faster R-CNN has three modules such that the base model which is a fully connected network proposes the feature maps, the second module identifies all the regions of interest and the third model detects the exact objects present in the regions proposed by the second model [7]. This paper uses a pretrained VGG-16 network as a base convolutional network to propose the regions and the Fast R-CNN for object detection [8,9].

The proposed CAD system uses a mini-MIAS database as an experimental dataset, a subset of MIAS database. The Mini-MIAS database has 330 digitized mammographic images at 50-micron resolution. Its resolution has been reduced to 200-micron resolution of 1024 x 1024 pixels and was made available by the Pilot European Image processing Archive (PEIPA) as mini-MIAS database [10].

Materials and Methods:

A. Problem Definition

Identifying breast cancer early and getting relevant cancer treatment are the most important strategies to prevent deaths from breast cancer. Breast cancer can be easily treated successfully, if it is found early and when it is small and is not spread. Regular screening is one of the best methods for early breast cancer detection.

A mammogram is a special radiogram which allows a radiologist to examine the abnormalities in the breast tissue. Before mammography became prevalent as a breast cancer screening modality, most breast cancers were being diagnosed by palpation (feeling an object in our body) [11]. The mammography breast image is generated by exposing the breast to lower amounts of radiation. The abnormalities of the breast which are caused by cancer, fatty cells or other conditions like cysts can be shown as a lump in the digitized mammogram images. The micro-calcifications which are tiny clusters of calcium are even exposed in the digitized mamo-images.

Diagnostic Mammography is vital in early detection of about 75% of breast cancers, before the patient realize that they are affected by breast cancer. Hence mammographic test is significant to reduce the risk and the mortality of the breast cancer [12].

CAD for mammography is intended to support radiologists in identifying elusive cancers which might otherwise be missed. CAD software assisted radiologists to improve diagnosis and accurate prediction in the screening of mammography which is used in the actual clinics from the 1990s. CAD identifies and marks potential abnormal areas on the digitized mamo-images. Screening mammograms by CAD is approved by the US Food and Drug Administration (FDA) in 1998 and in USA 5% of screening mammograms were analyzed by using CAD [13]. Once the Centers for Medicare and Medicaid Services (CMS) increased reimbursement for CAD in 2002, nearly 74% of all screening mammograms in the Medicare population were analyzed with CAD in 2008.

B. Related work

The advanced development of various machine learning and deep learning approaches has created a lot of interest in solving medical imaging problems using these techniques. The challenge of image classification task in mammography images is to identify the tiny tumor cells. Although classification of manually annotated ROIs is an important first step, a CAD system must be able to operate on the entire mammogram to provide additional information beyond the known lesions and enhance clinical interpretations. The annotated mamo-images in mammography databases made easy to make use of object detection and classification methods like region-based convolutional neural network (R-CNN) and its variants [14 - 16].

A recent research study shows that using DL methods drop human error rate for breast cancer diagnoses by 85% [17]. Currently CNN models are designed in such a way that improves radiologists' ability to find even the smallest breast cancers at earliest stages. This facilitates alerts to the radiologist for the need of further analysis [18]. Research studies shows that CNNs provide additional description for minute lesions which helps the radiologist for the better diagnosis and accurate prediction [19]. This advancement in CNNs facilitate automatic diagnosis system for mamo-images in future.

The availability of large public data repositories, high-end GPU/CPU processors and the power of parallel/distributed computations helped in various image analysis tasks like pattern recognition and classification by using CNNs. The limitation of using CNN in medical image analysis is the requirement of large numbers of expert annotated data for training the models. This limitation can be overcome by using transfer learning and augmentation techniques [20].

c. Data

The experimental dataset mini-MIAS database has 330 digitized mammograms. Out of these 330 mammographic images, 67 are proven to be benign, 54 are malignant and 209 are normal. The experimental dataset also consists of other findings like classes of abnormalities present in the image, their positions and the types of breast tissue i.e., Fatty, Fatty-glandular and Dense-glandular.

d. Methods

This paper proposes an automatic breast cancer lesion identification on digitized mammographic images using deep learning techniques. Generally, CNNs contain a stack of two or more layers like an input layer, a hidden layer and an output layer. One or more convolution layers, pooling layers and fully connected layers are part of CNNs' hidden layer. Currently object detection networks primarily depend on algorithms which propose regions. This paper proposes an advanced CNN based object detection system Faster R-CNN for the lesions detection in digitized mamo-images. The Faster R-CNN has a base network, RPN and an object detection network, Fast R-CNN.

RPN is a fully connected convolutional network which bounding boxes for the objects based on the high probability scores at each position in the training image. RPN shares full-image convolution features with Fast R-CNN which helps to detect the objects. Object detection networks detect the object locations using region proposal algorithms. These region proposal algorithms generate bounding boxes where the probability of presence of objects in that region are high. These bounding boxes are produced by RPN by performing convolution operation on feature maps. These feature maps contain the dominant features of the expert annotated input image. These feature maps are produced by the base network VGG-16.

e. CNN Training & Pre and Post Processing Methods

All the 121 abnormal (67 benign and 57 malignant) mammogram images have been downscaled to tiles of size 600 x 600 pixels for the faster training. Dataset is split into a training set of 106 images and a testing set of 15 images. The text files associated with both training and testing sets comprising the image path along with its class label and the ground truth have been prepared.

Two modules of Faster R-CNN have three parts namely the base network, region proposal network and a classifier layer. The base network used by the model is VGG16 which has 16 layers [21]. This base model used for training was pretrained on 1.2 million images from the ImageNet dataset. The feature Map given by this network is passed to the region proposal network and classifier layer, as illustrated in Figure.[1]

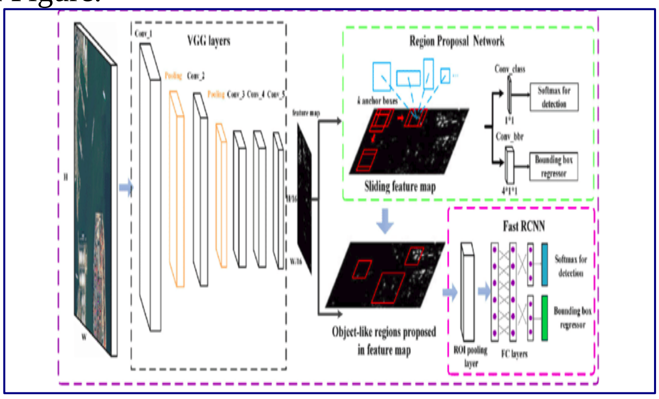

Fig. 1. VGG16 Model

RPN is a small convolutional neural network which uses the feature map produced by the base network and proposes regions/bunch of boxes (anchors) to detect the presence of objects. To be more precise, RPN predicts the possibility of an anchor being background or foreground and refine the anchor as illustrated in Figure.[2] The regions whose score crosses the threshold value will be passed to the Fast R-CNN classifier.

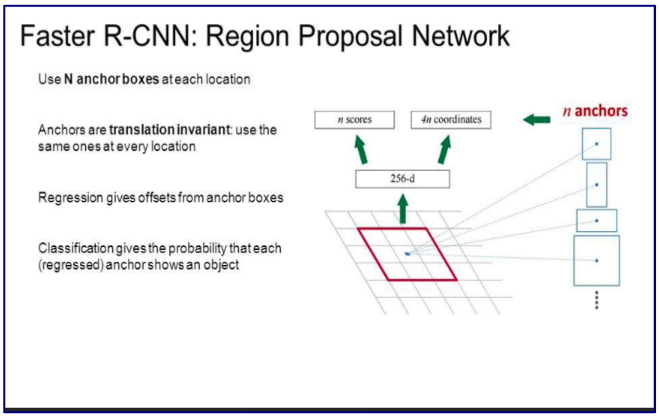

Fig. 2. Faster R-CNN: Region Proposal Network

Before the regions of different sizes proposed by RPN, they go through transformation at ROI pooling layer where it produces fixed size feature maps by doing max pooling as illustrated in Figure.[3] From the overlapping boxes the best predictions are selected using non-max suppression [22].

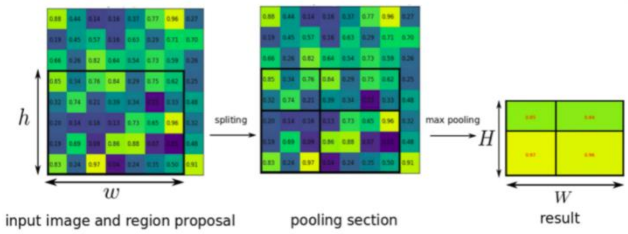

Fig. 3. Faster R-CNN: Region Proposal Network

The objects (lesions) in the mammographic images are very small in size than the objects present in the imageNet images. So, the proposed system reduced the object detection threshold value from 0.7 to 0.6. At classifier layer, the lesion bounding boxes (regions) proposed by RPN are regressed and classified into labels as either Malignant and Benign.

Results and Discussion

The experimental dataset mini-MIAS database has 121 abnormal mammogram images. The proposed network Faster R-CNN has been trained using the base network VGG16 and generated feature map. The generated feature map by the base network has been passed to RPN. RPN uses this feature map to propose regions/bunch of boxes for detecting the objects presence. The regions whose score crosses the threshold value will be passed to the classifier final layer. The classifier final layer further regresses and classifies the bounding boxes proposed by RPN into Normal, Malignant and Benign. The model generated 0.85 mAP value for the testing set of 15 images.

The accuracy of Faster-RCNN is defined as $\frac{true\ positives+true\ negatives}{true\ positives+false\ positives+false\ negative+true\ negative}$ which measures all the correctly identified cases. With imbalanced datasets, there are chances that despite having good accuracy models may fail to identify critical regions. In those scenarios, other metrics like dice, Jaccard coefficients and F1-score are used to assess the model.

Any CNN model initially learns the features from the training data. After fitting the training data well, the model tries to generalize and make accurate predictions for the incoming new data. If the model trains data too well it runs into an overfitting problem. Overfitting learns the best features and the noises of the image leads to wrong predictions which affects the accuracy of the model. Overfitting can be overcome by doing cross validation of splitting the data set into training and testing data. Using the training set the model is trained and its prediction performance is evaluated using the validation set. To do an unbiased evaluation on the final model the testing set is applied on the model.

Faster-RCNN was run on the test data and generated a list of bounding boxes with associated confidence scores. There is a presence of an object inside the corresponding bounding box if the confidence score is greater than the given threshold value. A predicted box is declared as true positive if its IoU is greater than the threshold (0.5). Else, it is a false positive.

In models like faster R-CNN the end results are obtained after the combined performance of two tasks i.e., classifying the object (benign or malignant) and localizing (bounding box prediction). So, both the end results need to be taken into consideration for evaluating the model. The evaluation of these combined results can be done by a popular metric measure called mAP (mean Average Precision).

Recall and precision curve was computed for the threshold and the area under this curve is said to be the Average Precision (AP). AP was then calculated for both benign and malignant classes and averaged to yield the mean Average Precision (mAP) which takes the values between 0 and 1. The proposed system is resulted with 0.85 mAP value.

F1-score is a harmonic mean of Precision and Recall. It provides a better measure than Accuracy metric with incorrectly classified cases. In most and highly complex real-life classification problems like medical imaging analysis, imbalanced class distribution exists and thus F1-score is a better metric to evaluate the model. The proposed system has achieved a F1-score of 0.6896 as shown in Table.[1]

Table 1. Testing Metrics

F1-Score	Precision	Recall
0.68	0.58	0.83

The proposed model detected lesions with corresponding class label and corresponding class scores shown as red box and are compared with the actual ground truth label shown as green box, which are illustrated in Figure.4

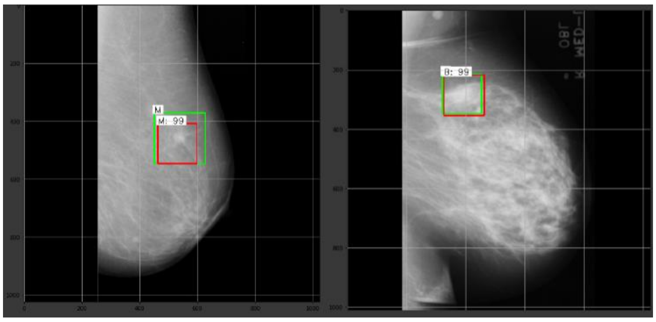

Fig. 4. The model detected lesions with corresponding class label and class scores (Red box) are compared with the actual ground truth label (Green box)

The paper proposes future work to include CBIS-DDSM database.26 DDSM has been updated and standardized to CBIS-DDSM.27 The DDSM database has 2,620 mammography images which includes normal, benign, and malignant cases. CBIS-DDSM database has expert annotated dataset. Also, this database has mammographic images which have been decompressed and converted into DICOM format, the updated ROI segmentation and bounding boxes and the respective class labels. The proposed system produced decent results in detecting mammographic lesions. Though the traditional Faster R-CNN fails to detect several smaller objects, by adjusting few parameters like reducing the anchor box scales and the RPN overlapping values worked better than the traditional Faster R-CNN in detecting the smaller lesions. The other problem with smaller objects is that the network might forget the features learned in the initial stages. An approach which propagates the features learned in the starting layers to the last layers should be implemented. This can be done using the residual network as the base network.

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