Premature Detection of Breast Carcinoma with Increased Accuracy

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***Abstract*— This work proposes a novel approach to the initial lesion detection in ultrasound breast images. The objective is to automate the manual process for the Region Of Interest (ROI) labeling in Computer-Aided Diagnosis (CAD). We propose the use of hybrid filtering, multifractal processing, and thresholding segmentation in the initial lesion detection and automated ROI labeling. We are supposed to use the ultrasound breast images to evaluate the performance of the proposed approach. Images are pre-processed using thresholding segmentation which is applied on the image. Finally, the initial lesions are detected using a rule-based approach. The accuracy of the automated ROI labeling is improved .We compares the performance on the proposed method of Improved Fully convolutional Network(FCN) Alexnet . We conclude that the proposed method is more accurate and performs more effectively than the benchmark algorithms considered.**

***Keywords*— Breast cancer, convolutional neural networks, lesions detection, transfer learning, ultrasound imaging.**

I. INTRODUCTION

Breast cancer is the most common of all cancers affecting women in the developed countries. In the United Kingdom, more than 41,000 cases are diagnosed annually, and it is predicted that 1 in every 9 women will develop breast cancer at some point in life. Early detection plays a significant role in the fatality of breast cancer[1]. Technologies that aid in the early detection of cancers are therefore attracted much attention from the research community.

II. MAMMOGRAPHY

Mammography and ultrasound imaging are the standard technologies used in cancer screening. Mammography is accepted as the “gold standard” for breast imaging which is commonly used as the primary tool for cancer screening. However, in diagnostic workup, mammography and breast ultrasound are often used as complementary investigations. Mammography has been shown to cause high false-positive rates in diagnosis, and the radiation dose to the breast is harmful[2]. Further, cost considerations have resulted in most countries that is choose to use screen film mammography instead of a digitized version. However, the inability to change image contrast or brightness, problems in detecting subtle soft-tissue lesions (dense glandular tissues), and difficulties with archiving have limited the application of screen film mammography.

A. EXISTING SYSTEM

Deep learning is a representation learning method that will automatically discover features suited for a particular task from the raw data. The feature extractors are task-specific, in that they are not fixed to a set of specific rules each time .Each network contains multiple layers that lead to hierarchical features used in the learning process.

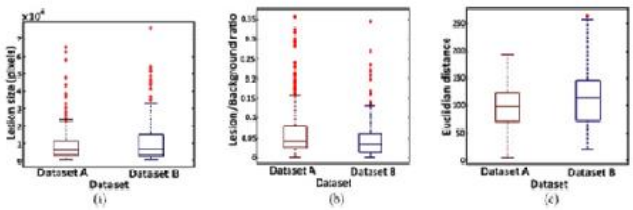

Fig.1. Box plot chart comparing the lesion size, .the ratio between the area of the lesion and the area of the image and the distance from the image centre to the lesion centroid.

Convolutional Neural Networks (CNNs) have become an important technique in image analysis, particularly in detection or recognition of faces , text, human bodies and biological images. However, it has not been used in breast ultrasound lesion detection[3]. For these reasons, we study the performance of CNNs in breast ultrasound lesion detection.

CNNs consist of convolutional layers and pooling layers, where the role of the former is to extract local features from a set of learnable filters and the role of the latter is to merge neighboring patterns, reducing the spatial size of the previous representation and adds spatial invariance to translation[4] .

CNNs are hierarchical neural networks and their accuracy is dependent on the design of the layers and training methods.

In most existing breast screening approaches, the “initial lesion”—that is, a suspect region— is manually located by a trained radiologist in a pre-processing stage by marking its topmost, leftmost, bottommost, and rightmost boundary limits with crosses. These crosses (and hence the initial lesion) are then manually encompassed within a rectangular region of interest (ROI)(by the radiologist and subsequently presented to a computer-aided diagnosis (CAD) system for further analysis leading to the segmentation and classification of the tumor.

Related Work

Automated Breast Ultrasound Lesions Detection Using Convolutional Neural Networks -Moi Hoon Yap , Member, IEEE, Gerard Pons, Joan Mart´, Sergi Ganau, Melcior Sent´ıs,Reyer Zwiggelaar, Adrian K. Davison, Member, IEEE, and Robert Mart for the results demonstrate an overall improvementby the deep learning approaches when assessed on bothdatasets in terms of True Positive Fraction, False Positivesper image, and F-measure.

B. PROPOSED SYSTEM

Our current research focus is to provide the radiologist with an automated tool that can effectively assist in the selection of the ROI and in improving the consistency of interpretation. However, it is worthwhile noting that the automatic detection of ROIs is not meant to replace the radiologist, but to provide a tool to reduce the radiologist's ROI labeling time and to warn of possible ROIs that might otherwise be missed because of the poor quality of the ultrasound image.

A. Preprocess-otsu segmentation

Converting a grey scale image to monochrome is a common image processing task[5]. Otsu's method, named after its inventor Nobuyuki Otsu, is one of the binarization algorithms. Image segmentation is the fundamental approach on digital image processing. Among all those segmentation methods, Otsu method is one of best methods for image thresholding due to its simple calculation. Otsu is an automatic threshold selection region based on the segmentation method. This paper studies various Otsu algorithms.

B. Contrast enhancement

The contrast enhancement technique plays a vital role in image processing inorder to bring out the information that exists within low dynamic range of that gray level image. In order to improve the quality of an image, it is required to perform the operations such as contrast enhancement and reduction or removal of noise.

C.K-means clustering segmentation

Clustering is a method to divide a set of data into a specific number of groups[6].

- It is most probably called as k-means clustering. In k-means clustering, it partitions a set of collection of data into a k number group of data11, 12 that classifies a given set of data into k number of disjoint cluster.
- K-means algorithm consists of two separate phases. In the first phase it calculates the 'k' centroid and in the second phase it takes each point to the cluster which has nearest centroid from the respective data point.
- There are different methods to define the distance of the nearest centroid among those one of the grouping is ended it recalculates the new centroid of each cluster and based on that centroid, a new Euclidean distance is calculated between each center and each best method is Euclidean distance.
- Once the data point and that assigns the points in the cluster which have minimum Euclidean distance. Each cluster in the partition distinct by its member objects and also by its centroid.

The centroid for each cluster is the point to which the sum of the distances from all the objects in that cluster is minimized. So K-means is an iterative algorithm in which it depreciates the sum of the distances from each object to its cluster centroid, over all clusters.

Let us consider an image with resolution of x×y and the images have to be cluster into k number of cluster. Let p(x, y) be an input pixels which is to be cluster and ck be the cluster centers.

The algorithm for k-means13 clustering is following as:

1. Initialization of number of cluster k and centre.
2. For each pixel of an image, calculate the Euclidean image using the relation given below

$$d = \|p(x,y) - c_k\|$$

(1)

3. Allocate all the pixels to the nearest centre based on distance d.
4. After all pixels have been assigned, recalculate new position of the centre using the relation [6]given below

$$c_k = \frac{1}{k}\sum_{y\in c_k}\sum_{x\in c_k} p(x,y)$$

(2)

5. Replicate the process until it satisfies the tolerance or error value.
6. Reshape the cluster pixels into image.

Although k-means has one of the greatest merits such as being easy to implement, it has some drawbacks. The quality of the final clustering results depend on the arbitrary selection of initial centroid. So if the initial centroid is arbitrarily chosen, it will acquire different result for different initial centers. So the initial center will be suspiciously chosen so that we obtain our desire segmentation. And also computational complexity is another term which should be consider while designing the K-means clustering. It depends on the number of data elements, number of clusters and number of iteration.

C. IMPROVED DEEP LEARNING FCN ALEXNET NEURAL NETWORK

This neural network consists of the following distinct layers: two layers of tied convolution with max pooling, cross-input neighborhood differences, patch summary features, across-patch features, higher-order relationships, and finally a softmax function to yield the final estimate of whether the input images are of the same cell or not. Each of these layers is explained in the following subsections.

A.Tied Convolution

To determine whether two input images are of the same cell, we need to find relationships between the two views. In the deep learning literature, convolutional features have proven

to provide representations that are useful for a variety of classification tasks.
The first two layers of our network are convolution layers, which we use to compute higher-order features on each input image separately. In order for the features to be comparable across the two images in later layers, our first two layers perform tied convolution, in which weights are shared across the two views, to ensure that both views use the same filters to compute features.
In the first convolution layer we pass input pairs of RGB images of size 60 × 160 × 3 through 20 learned filters of size 5 × 5 × 3. The resulting feature maps are passed through a max-pooling kernel that halves the width and height of features. These features are passed through another tied convolution layer that uses 25 learned filters of size 5 × 5 × 20, followed by a max-pooling layer that again decreases the width and height of the feature map by the factor of 2. At the end of these two feature computation layers, each input image is represented by 25 feature maps of size 12 × 37.

B.Cross-Input Neighborhood Differences
The two tied convolution layers provide a set of 25 feature maps for each input image, from which we can learn relationships between the two views[2]. Let fi and gi , respectively, represent the 'i' th feature map ($1 \leq i \leq 25$) from the first and second views.

C.Patch Summary Features
In the previous layer, we have computed a rough relationship among features from the two input images in the form of neighborhood difference maps.
A patch summary layer summarizes these neighborhood difference maps by producing a holistic representation of the differences in each 5 × 5 block. This layer performs the mapping from K ∈ R 12⇥37⇥5⇥5⇥25 → L ∈ R 12⇥37⇥25. This is accomplished by convolving K with 25 filters of size 5 × 5 × 25, with a stride of 5.
By exactly matching the stride to the width of the square blocks, we ensure that the 25-dimensional feature vector at location (x, y) of L is computed only from the 25 blocks Ki(x, y), i.e., from the 5×5 grid square (x, y) of each neighborhood difference map Ki (where $1 \leq i \leq 25$).
Since these are in turn computed only from the local neighborhood of (x, y) in the feature maps fi and gi , the 25-dimensional patch summary feature vector at location (x, y) of L provides a high-level summary of the cross-input differences in the neighborhood of location (x, y)[2]. We also compute patch summary features L 0 from K0 in the same way that we computed L from K.
Note that filters for the mapping K → L and K0 → L 0 are different, not tied as in the first two layers of the network. Both L and L 0 are then passed through a rectified linear unit (ReLu).

D.Across-Patch Features
So far we have acquired a high-level representation on the differences within a local neighborhood, by computing neighborhood difference maps and then acquiring a high level local representation of these neighborhood difference maps.
In the next layer, we find out the spatial relationships across neighborhood differences. This is done by convolving L with 25 filters of size 3 × 3 × 25 with a stride of 1.
The resultant features are passed through a max pooling kernel to reduce the height and width by a factor of 2.
This yields 25 feature maps of size 5 × 18, which we denote M ∈ R 5⇥18⇥25. We similarly obtain across-patch features M0 from L0[2] . Filters for the mapping L → M and L 0 → M0 are not tied.
Higher-Order Relationships that we apply a fully connected layer after M and M0 . This captures higher-order relationships by a) combining information from patches that are far from each other and b) combining information from M with information from M0 .
The resultant feature vector of size 500 is passed through a ReLu nonlinearity[2]. These 500 outputs are now passed to another fully connected layer containing 2 softmax units, which represent the probability that the two images in the pair are of same cell or different cell .

E.Training the Network
We pose the re-identification problem as binary classification. Training data consists of image pairs labeled as positive (same) and negative (different). The main objective is average loss over all pairs in the data set. As the data set can be quite large, in practice we use a stochastic approximation of this objective.

Training data are randomly divided into mini-batches. The model performs forward propagation on the current mini-batch and computes the output and loss. Back propagation is then used to compute the gradients on this batch, and network weights are updated.

We perform stochastic gradient descent to perform weight updates. We start with a base learning rate of η (0) = 0.01 and gradually decrease it as the training progresses using an inverse policy: η (i) = η (0)(1 + γ · i) −p where γ = 10−4 , p = 0.75, and i is the current mini-batch iteration.
We use a momentum of μ = 0.9 and weight decay λ = 5 × 10−4 . With more passes over the training data, the model improves until it converges. We use a validation set for evaluating the intermediate models and select the one which exhibits maximum performance. See the supplementary material for performance on the validation set as a function of mini-batch iterations.

F.Data Augmentation
There are not nearly as many positive pairs as negative pairs, which can lead to data imbalance and over fitting. To reduce over fitting, we artificially enlarge the data set using label-preserving transformations . We augment the data by performing random 2D translation, as well done. For an original image of size W × H, we sample 5 images around the image center, with translation drawn from a uniform distribution in the range [−0.05H, 0.05H]× [−0.05W, 0.05W]. For the smallest data set , we also horizontally reflect each image

G.Hard Negative Mining

Data augmentation increases the number of positive pairs, but the training data set is still imbalanced with many more negatives than positives. If we trained the network with this imbalanced data set, it would learn to predict every pair as negative. Therefore, we randomly down sample the negative set to get just twice as many negatives as positives (after augmentation), then train the network. The converged model thus acquired is not an optimal since it has not seen all possible negatives[2]. We apply the current model to classify all the negative pairs, and identify negatives on which the network performs worst. We retrain the fully connected (top) layer of the network using a set containing as many of these difficult negative pairs as positive pairs1 .

H.Fine-tuning

For small data sets that contain too few positives for effective training, we initialize the model by training on a large data set[2]. After hard negative mining on the large set, the parameters of the converged model are now adapted on the new, small data set. For this new network learning, we begin stochastic gradient descent with learning rate η (0) = 0.001 (which is 1/10th the initial pre-training rate)

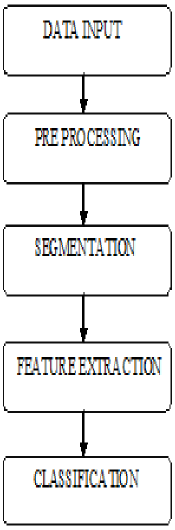

Fig.2. Flowchart of Proposed method

Principle of operation: The breast lesion detection involves mainly three steps:enhancement(conversion of original image into grayscale),segmentation (conversion of grayscale into binary) and classification(classifies the tumour and non-tumor cells based on their features)

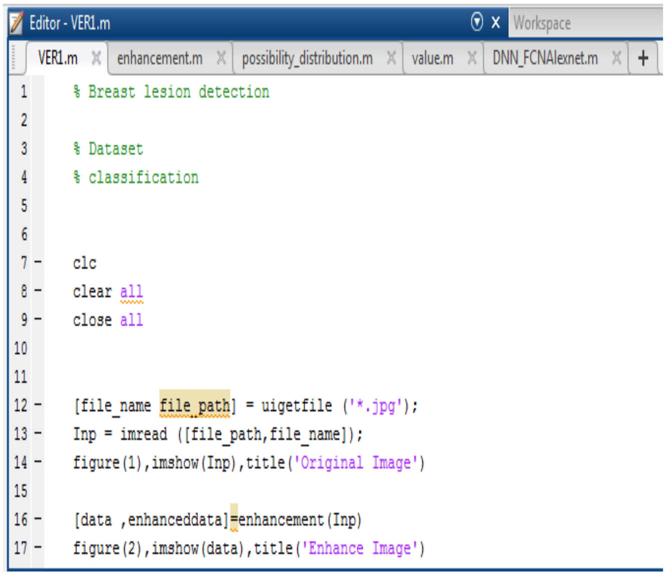

Fig 3.Program to detect breast carcinoma

RESULTS AND DISCUSSIONS

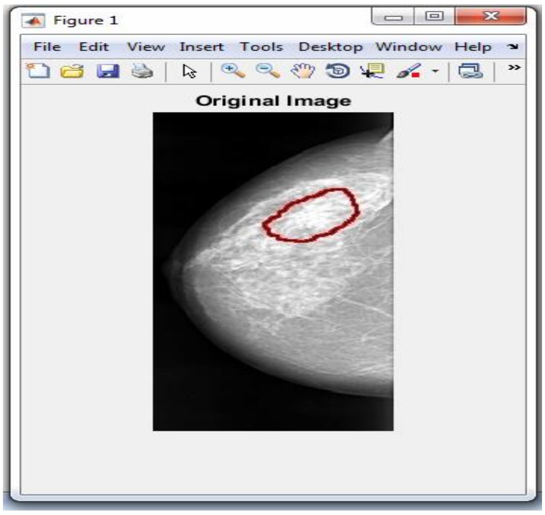

Fig 4. Explains the original image of the breast

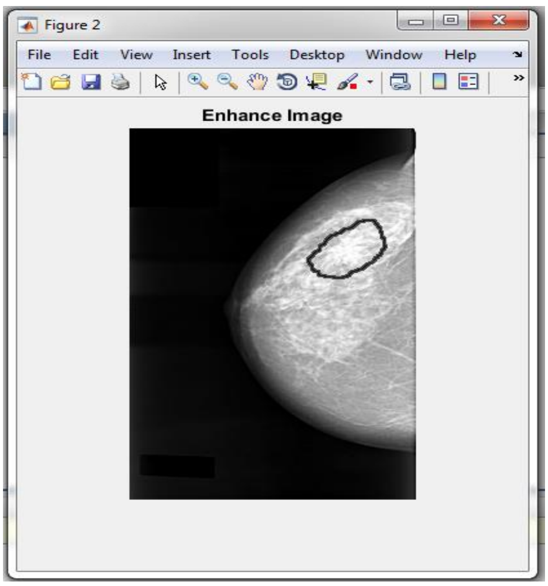

Fig 5. Describes the enhanced image from the original image

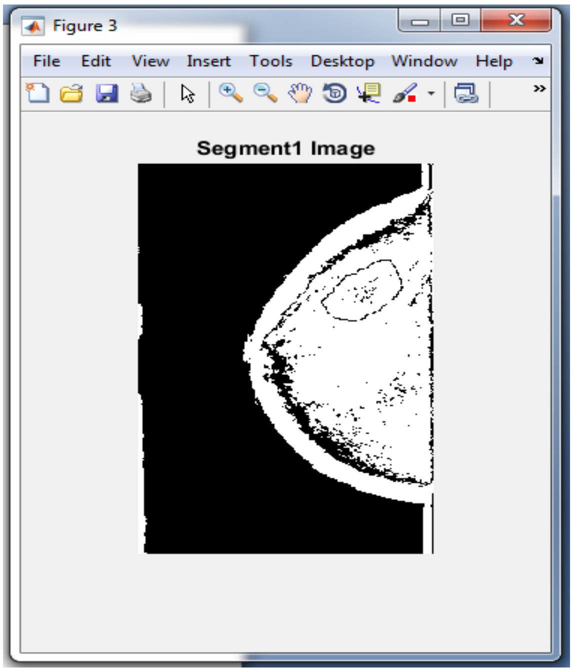

Fig 6. Demonstrates the image which is segmented from the enhanced Image

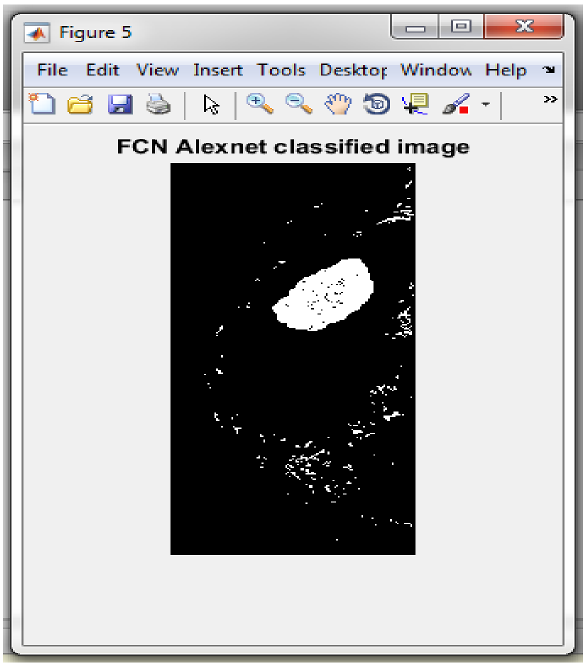

Fig 7. Defines the classified image from the pre-processed methodologies

CONCLUSIONS

The proposed work investigated the use of deep learning approach Transfer Learning (FCN-AlexNet) and a The performances were evaluated on datasets in terms of TPF, FPs/image and F-measure. In this paper, the Transfer Learning FCN-AlexNet achieved the best results for Dataset in terms of FPs/image and F-measure. Deep learning methods are adaptable to the specific characteristics of any dataset, since these are machine-learning based and a particular model is constructed for each dataset. For further research, it is our assertion that deep learning approaches could be adapted to other medical imaging techniques .Lesion detection is the initial step of a CAD system. Hence, proposed work focused on increasing the accuracy by adding more training data, extending our works to breast ultrasound lesion segmentation and classification, and evaluate the performance of the complete CAD framework.

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