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Diagnosis of Mammographic Images for Breast Cancer Detection using FF-CSO Algorithm

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Abstract: Many diseases in the human being are can be detected through different imaging technology. The mammography is one of the imaging technique through which breast cancer cells can be identified. The mammographic breast image is preprocessed for eradicating the pectoral muscle in the breast cancer identification that contains a mammogram for encircling the process of detection. The cancer tissues having higher pixel intensities can be detected easier than the remaining breast region. It is difficult to classify the breast tumor tissues into malignant and benign ones. The mammographic breast image is generally pre-processed to eliminate pectoral muscle for the optimal diagnosis. Further, the active contour based segmentation is done to separate out the cancer region from entire mammographic image acquired by special technique. Segmenting accurate region of cancer will help in classification so segmentation stage has its own importance. Two different optimization algorithms are merged to improve optimization accuracy. The algorithms considered are Firefly and chicken swarm optimization (FF-CSO) is used optimize feature set and optimize error function of DBN. Once segmentation is performed on the image, the next process is to extract features from that segmented region to collect useful information for distinguishing the cases. In this we extracted LBP features from the segmented images. The deep learning architectures is for classification.

Key words: LBP, Active contour, DBN, breast cancer. Mammographic,

I. Introduction

The breast cancer represents a main health issue affecting women in many of the countries. The second most diagnosed disease in the world is the breast cancer. There exist two

forms of breast cancers like "Mediolateral Oblique and Cranial Caudal. The complication in the breast cancer is the tissues in the breast are very densely organized. The densely organized tissues creates problem in detection process. It usually starts in the ducts, tubes that convey milk to the nipple as well as lobules, organs that generate milk. Before reaching a tangible format, the vast portion of breast tumours is metastasized. Distinct imaging approaches are developed for identifying the cancer in the tissue level. These are framed as Mammography and Infrared Imaging. In the previous years, thermography or infrared imaging is one among the optimal routines for the breast cancer detection as it records the improved cancer stages. It describes an efficient approach for the initial step breast cancer detection. Some of the routes for diagnosing as well as recognizing the breast cancer are the biopsy (open surgery), mammography, clinical breast exams, and self-examination. Mammography is better due to the fact that it is appropriate than the self-examination, less harmful, and is sheltered.

II. Literature Review

Wang *et al.* [1] have provided an novel 3D convolutional network. It was employed for detecting the cancer automatically. A densely deep supervision technique augments the sensitivity of detection with the help of the multi-layer features. A threshold loss addressed pixel-level

adaptive threshold that described the cancer with non-cancer for attaining high sensitivity with less false positives.

Zheng *et al.* [2] have looked into using CNN-based approach. The deep learning architecture consisted of numerous "convolutional layers, Max-pooling layers, and Long Short-Term Memory". The "error estimation, as well as classification", was included in a softmax as well as a fully connected layer. It joined the machine learning techniques with the feature selection approaches.

Wang *et al.* [3] have described a breast cancer detection using CAD technique on the basis of feature fusion with CNN deep features. Initially, a mass detection technique was developed on the basis of unsupervised method clustering and CNN deep features. In the second step, density, texture, morphological, and deep features were constructed. In the third step, an ELM classifier was proposed for classification.

Zhang *et al.* [4] have labeled a technique of tomo-synthesis and mammogram classification on the basis of CNNs. Distinct CNN methods classified the 3-D tomo-synthesis and 2-D mammograms and each classifier was defined in terms of truth-values produced by the histology outcomes.

Nasir *et al.* [5] have addressed "Multi-View Feature Fusion (MVFF)" on the basis of CAD system. It was composed of three stages. The initial stage classified it into "normal or abnormal". The second step classification of calcification or mass. The final stage performed the benign or malignant classification. The feature extraction methods on the basis of CNN functioned on every view in a separate manner.

In 2019, Shen *et al.* [6] have addressed a mixed-supervision guided technique and residual cyclic unpaired encoder-decoder network for the purpose of benign-malignant classification and joint segmentation. The strong supervision was coupled in the format of segmentation mask, and the weak supervision was coupled in the form of benign-malignant label via an easier annotation process.

Hoon *et al.* [7] have developed the utilization of deep learning approaches for detecting the breast lesion and examined three various approaches like a "transfer learning approach, a U-Net, and a Patch-oriented LeNet with a pre-trained FCN-AlexNet". It was compared to the "Deformable Part Models, Rule-oriented Region Ranking, Multifractal Filtering, and Radial Gradient Index". The outcomes retrieved better with respect to F-measure, False Positives per image, and True Positive Fraction

III. Proposed Methodology

i) ***Preprocessing:*** Preprocessing is done using "Contrast Enhancement using Histogram Equalization**"** It gains a higher contrast by allowing the areas of lower level local contrast of images and is expressed in Eqn.1

$$PDF = \rho(in_k) = \frac{in_k}{tp} \tag{1.1}$$

Where tp is the total pixels in an image and in_k is denotes the total pixels with intensity k

ii) ***Segmentation:*** Segmentation is carried using Active Contour method. This is implemented by considering the energy constraints to divide the region of interest in images. It can be applied in different applications such as motion tracking and stereo tracking because of the advantages of active contour.

$$PC(x) = [Q(x), U(x)] \tag{1.2}$$

iii) ***Feature Extraction*****:** It extracts the texture feature from the images. LBP [5] is competent owing to the computation simplicity, low difficulty levels, and superior discriminative power. LBP can be generally performed in diverse applications such as facial expression recognition, medical imaging, and object tracking. It takes a small window from the images and measures the differentiation in intensity among the center of the pixel with their neighbors, which is also considered on the perimeter of a circle. Furthermore, a pre-defined threshold is employed for encoding the distinctions of gray level intensity into binary structure. The attained binary bits are combined for generating a decimal value by specific weights. The local binary map is generated for a considered image through the substitution of center pixel with their binary pattern values. From each LBP value, the histogram is determined to form the feature vector. The LBP is formulated in Eq. (1.3)

$$LBP_{Np,Ra} = \sum_{np=1}^{Np} 2^{np-1} \times Su\left(xz_{np} - xz_{fp}\right) \tag{1.3}$$

$$Su(xz) = \begin{cases} 1 & , xz \geq 0 \\ 0 & else \end{cases} \tag{1.4}$$

Here, the fixed or center pixel is denoted as xz_{fp}, the neighboring pixels are termed as Np at a radius Ra, and the gray level intensity of its neighbors is considered as xz_{np} Fig.1. Shows architecture of proposed system.

iv) Feature Optimization:

Fire Fly updated Chicken Swarm Optimization Algorithm (FF-CSO)

The typical CSO is provoked by following the top-down order which usually exist in the chickens by their strength for finding their own food the open ground. This algorithm is more effective in determining solution for more complex problems. The scenery of chickens are monitored by the different rules. In the case of chicken swarm, several groups habitually exist in a dominant rooster, a some hens and the chicks exist in every group. The chicken swarms are divided according to the fitness values of chickens. The most terrible fitness values are called as chicks whereas the finest fitness values are known as roosters, and others are denoted as hens.

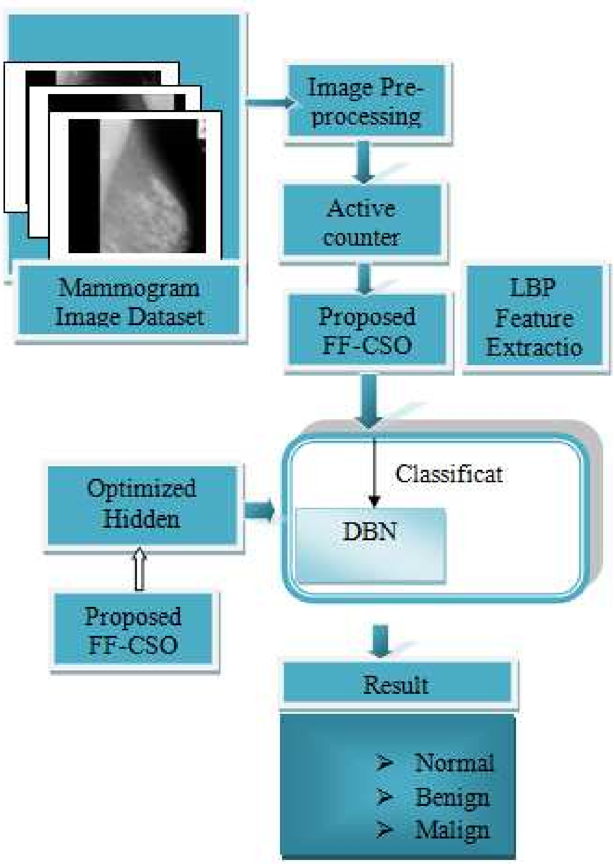


Fig.1 Block diagram of proposed system

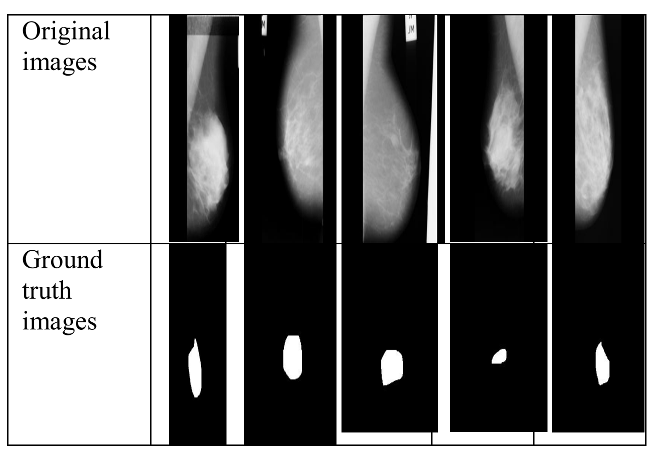
The existing CSO algorithm has the ability to get a high precision of convergence rate. But the problem of this algorithm is it has less number of cases in the searching time. This time will prolong in the discrete optimization problems. Hence, to operate with a high convergence rate, the beneficial concept of FF is used here. Modification of algorithm is represented in Eqn. (1.5)

$$X(in)p,q = Xp,\min + rndm\ (Xp,\max - Xp,\min),\ p = 1, 2,..,D \quad (1.5)$$

Classification: The DBN classifier which another form of neural network is used for classification of breast cancer. DBN is a kind of deep NNs comprising of several number of layers. Each layer contains several visible neurons in the input layer and the hidden neurons in the output layer. The major thing in DBNs are Boltzmann Machines which has important function of selecting the weights on the neurons so as get the finest results. In this proposed method the training of DBN is done by both RBM and proposed FF-CSO in order to decrease the error function so as to get more accurate results of classification.

IV. RESULTS and Discussion

The revealing of breast cancer from mammogram images is a difficult task since the tissues are densely organized. In the segmentation there may non-cancer region included so extraction features plays a very typical role. In the dataset the ground truth of segmented part of cancer region is given so we compared the ground truth, and other authors segmented images for the same dataset with detection parameters. Fig.2. shows segmentation results in comparison with ground truth. Fig.3, shows comparison of performance of the proposed algorithm on LBP feature with proposed optimization algorithm on DBN classifier. Table1, depicts classification mammographic images with different features on DBN classifier



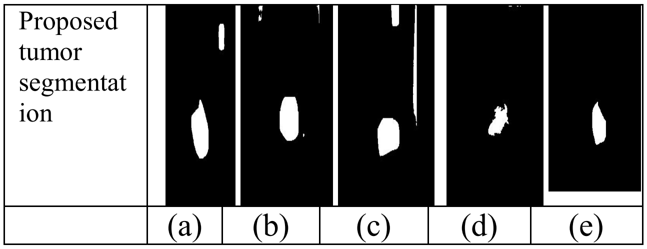


Fig.2. Segmentation results obtained

Table 1. Comparison of results with respect to different features sets

Measures	HOG	WLD	GLR M	GLCM	LBP
"Accuracy"	0.7882	0.7916	0.8576	0.8123	0.8611
"Sensitivity"	0.4583	0.4479	0.7083	0.7104	0.7395
"Specificity"	0.9531	0.9635	0.9322	0.9283	0.9218
"Precision"	0.8301	0.8600	0.8395	0.8812	0.8255
"FPR"	0.0469	0.0365	0.0677	0.0117	0.0781
"FNR"	0.5417	0.5521	0.2917	0.2196	0.2605
"NPV"	0.9531	0.9635	0.9322	0.9183	0.9218
"FDR"	0.1698	0.1400	0.1604	0.0917	0.1744
"F1-Score"	0.5906	0.5890	0.7683	0.8149	0.7802
"MCC"	0.5005	0.5121	0.6717	0.7135	0.6813

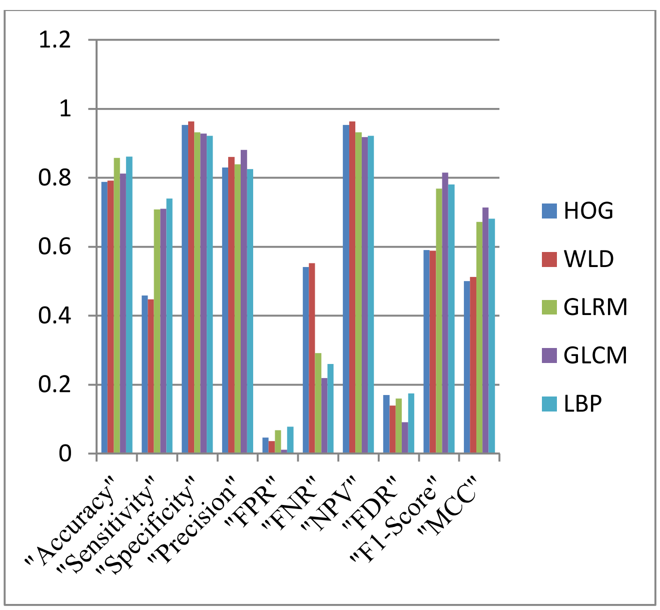


Fig.3. Comparison of performance

Conclusion

In the method proposed to find the existence of breast cancer using mammogram, there are mainly 4 steps noise removal by pre-processing, tumor segmentation, feature extraction from the tumor, feature optimization using a proposed hybrid optimization algorithm and finally classification. The tumor is segmented using an active contour method. Combination of two algorithms such as CSO and FF, called FF-CSO is used for optimization. The proposed hybrid optimization algorithm is effective in the process of optimizing the feature set obtained through LBP feature extraction. The optimization of features plays the crucial role in classifier. The feature set obtained by our proposed hybrid optimization algorithm is more effective. The error function of DBN is optimized using the proposed hybrid optimization (FF-CSO) algorithm. As weight function of DBN is optimized using the proposed algorithm, it is more faster is classification process, and also has better accuracy in classification process. The proposed method presents better accuracy in detection compared over various methods developed by several authors on this topic.

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