CLOUD COMPUTING-BASED FRAMEWORK FOR BREAST CANCER DIAGNOSIS USING EXTREME LEARNING MACHINE

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Abstract - Breast Cancer being a leading cause for deaths among women has now become major health concern. In order to increase the rate of survival, early detection of tumour is most important. Mammogram image segmentation and classification plays vital role in early detection. In this paper, Extreme Learning machine (ELM) method for classification is proposed and its performance measures are evaluated on Digital Database for Screening Mammography (DDSM) dataset and other existing like Support Vector Machine (SVM), Logistic Regression (LR) and Linear Discriminant Analysis (LDA) are also implemented for comparison analysis. It is found that ELM method gives better results.

Keywords - Breast Cancer, Classification, Elm, Local Binary Pattern (Lbp), Gray Level Co-Occurrence Matrix (Glcm), Gabor Features

I. INTRODUCTION

Breast cancer is the deadliest disease with a high fatality rate, which majorly affects women. Detection of cancer in its early stage is the only way to increase the survival rate which directly depends on accurate mammographic interpretation and analysis, which is very challenging. In order to assist radiologist in this challenging task many computer aided diagnostic (CAD) systems are developed. It includes machine learning and deep learning approaches which helps radiologists in identifying the subtle abnormality in mammogram images and to draw accurate conclusions which helps in further treatment. Mammogram images need enhancement in order to enhance low contrast images which further helps in proper segmentation and classification. Segmentation process finds the abnormality and locates it, after this classification can be done by categorizing the segmented images into one of many predefined categories.

Classification of mammogram images can be done using machine learning approaches which are based on supervised and unsupervised techniques. There are many machine learning and deep learning algorithms which include SVM, LR, Neural Networks (NN) and Deep Convolutional Neural Networks (DCNN). ELM is a feed forward neural networks which was invented by Guang-Bin Huang. It is a simple and efficient learning algorithm for training single hidden layer feed forward neural network (SLFNs). ELM has been extensively used in research for its advantage of less manual intervention, higher classification accuracy and less training time. For the better interpretation, the rest of the paper is organised as follows: section 2 discuss about related works, proposed methodology is detailed in section 3 followed by results and discussion in section 4 and finally concludes paper in conclusion section.

II. LITERATURE REVIEW

Enhancement can be done using spatial or frequency domain enhancement methods, namely logarithmic transformation [1], power-law transformation, histogram equalization [2,3,4,5,6], Bilateral filter [7,8], Butterworth filter [9], Gaussian filter [10], contrast limited adaptive histogram equalization [4,5,11]), median filter [12]. Pelin Gorgel et al. [13] presented a computer aided classification in classifying the segmented ROIs. It consists of three steps, first spherical wavelet transform (SWT) is applied on original ROIs then shape, boundary and grey level based feature of wavelet and scaling coefficients are extracted. Finally, classification of masses is implemented using SVM. Sobia Shakeel et al. [14] presented a new CAD technique, which relies on customized deep CNN to detect and classify breast cancer into malignant and benign. First region of interest (ROI) is extracted using region-based segmentation technique which is enhanced using contrast limited adaptive histogram equalization (CLAHE). Then, customized CNN is used to learn features from mammograms and later SVM is used to classify images. Venkat Kumar Hariraj et al. [15] presented Fuzzy multi-layer SVM (FM-SVM). It uses two steps, first extracting features based on texture and in step two, extracting features based on morphology. Combination of these effective features resulted in 98% of accuracy. M. Thilagaraj et al. [16] proposed DCNN for classifying the breast cancer images, which is optimized using artificial fish school optimization algorithm. This technique selects the training images by directly assigning them to the classifier. The proposed CNN model performs feature extraction, feature reduction and classification. Tariq Mahmood et al. [17] proposed a ConvNet and five DCNN architecture for diagnosing and classifying breast cancer masses. Here, transfer learning paradigm is used to enhance the pre-trained DCNN.

Some of the relevant research papers considered are mentioned here [18, 19, 20, 21]. It is found that machine learning approaches provides better segmentation and classification results. In next section, proposed method is explained in detail.

III. PROPOSED METHODOLOGY

In his section, the proposed method for classification of mammogram images is explained in detail. Here, the ELM method is used for classification. Block diagram for proposed method is shown in fig.1.

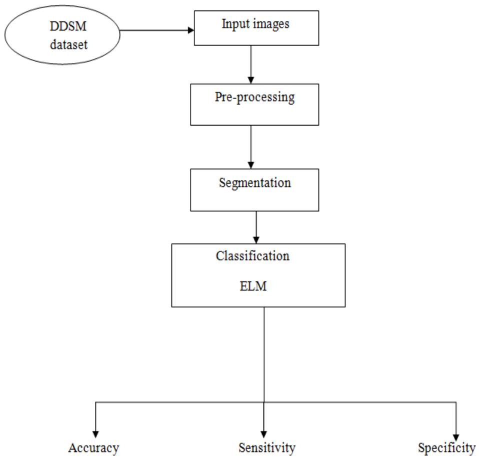

Fig.1. Block diagram for proposed method.

The dataset considered is DDSM dataset, images obtained from DDSM dataset is given as input for pre-processing, where the noise is removed and images are enhanced using contrast limited adaptive histogram equalization (CLAHE) in order to enhance the image's contrast and to preserve edges. The enhanced images are given for segmentation process, where U-net is used for segmenting the mammogram images. Finally, classification is done by using ELM method and its performance measure like accuracy, sensitivity and specificity are evaluated. ELMs are feed forward neural networks which can have single or multiple hidden layers of hidden nodes for classification. It is simple, robust and efficient algorithm. The model of ELM constitutes input layer, single hidden layer and output layer. The ELM model is shown in fig. 2.

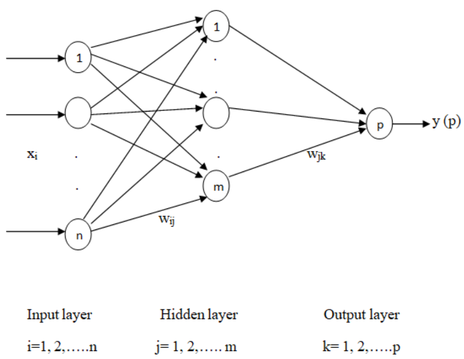

Fig.2. Single hidden layer feed forward ELM architecture.

$$y(p) = \sum_{i=1}^{m} \beta_j g\left(\sum_{i=1}^{n} w_{i,j} x_i + b_j\right) \quad .... \quad (1)$$

The model consists of n input layer nodes, m hidden layer nodes and p output layer nodes. Function g(x) is hidden layer activation function. β_j represents the weights between the input layer and the hidden layer and b_j represents the weights between the output layer and the hidden layer. As weight between hidden layer and output layer is the only parameter that is need to be learned. ELM converges much faster than traditional algorithm. Since, it learns without iterations. Results are discussed in the next section.

IV. RESULT AND DISCUSSIONS

The mammogram images are obtained from publicly available dataset DDSM. As the dataset considered was small with 200 images, larger dataset is created by augmenting the image using geometric operations, it also reduces the over-fitting problem. The images from dataset are normalized for future convenient use in segmentation and classification. The ground truth is also obtained from the same database. Fig. 3 shows cancerous and non-cancerous mammogram images.

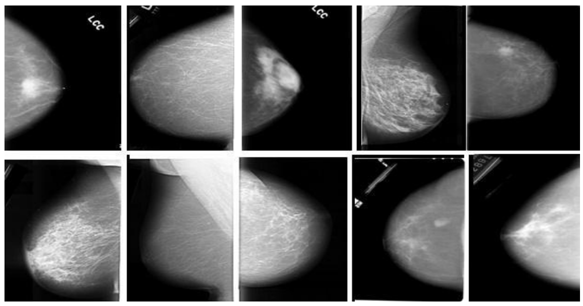

Fig.3. Tumor and Non-Tumor Images used for Classification.

LBP		GLCM					Gabor	
EG	ET	CT	DSS	HGT	EG	CR	EG	ET
0.44	1.81	5.50	0.95	0.74	0.59	0.99	0.50	1.62
0.31	2.20	7.86	1.43	0.63	0.45	0.99	0.41	1.71
0.33	2.12	8.37	0.97	0.71	0.46	0.99	0.45	1.47
0.39	1.97	5.99	0.80	0.74	0.51	0.99	0.70	0.93
0.48	1.68	3.11	0.62	0.80	0.63	0.99	0.53	1.48
0.26	2.36	8.61	1.72	0.57	0.38	0.99	0.29	2.30
0.41	1.90	7.62	0.91	0.74	0.55	0.99	0.53	1.36
0.53	1.57	8.02	0.89	0.78	0.65	0.99	0.75	0.87
0.50	1.64	6.88	0.88	0.77	0.63	0.99	0.78	0.77

0.35	1.97	8.33	0.74	0.52	0.52	0.99	0.47	1.43
EG: Energy DSS: Dissimilarity			ET: Entropy HGT: Homogeneity			CT: Contrast CR: Correlation		

TABLE I Measuring values obtained from feature extraction methods

LBP, GLCM and Gabor feature extraction algorithm are used to extract different features, which helps in classification of normal and cancerous mammogram images. The measured features obtained during feature extraction are given in table 2. Fig 3-5 give visual representation of LBP, GLCM and Gabor features extracted respectively.

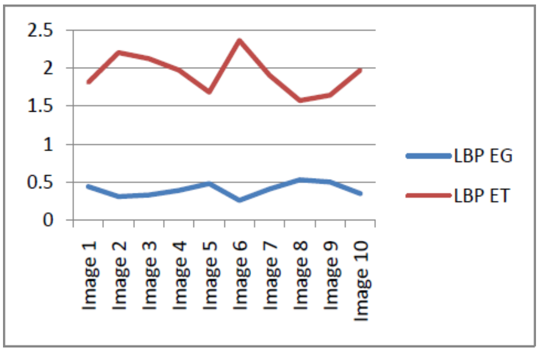

Fig.4. Visual Representation of proposed LBP feature extraction results.

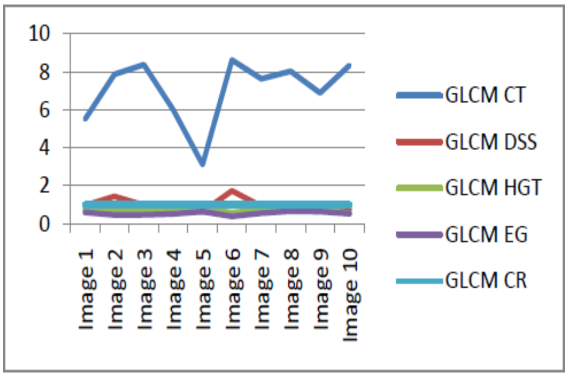

Fig.5. Visual Representation of proposed GLCM feature extraction results.

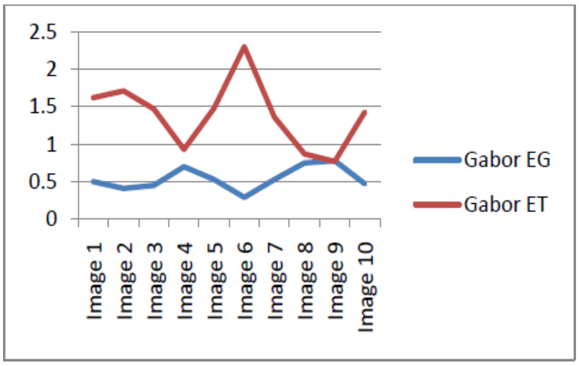

Fig.6. Visual Representation of proposed Gabor feature extraction results.

Classification Methods	Accuracy	Sensitivity	Specificity
SVM	0.73	0.75	0.67
LR	0.71	0.72	0.67
LDA	0.71	0.74	0.63
ELM	0.87	0.90	0.79

TABLE II Performance Measures for Different Classification Methods

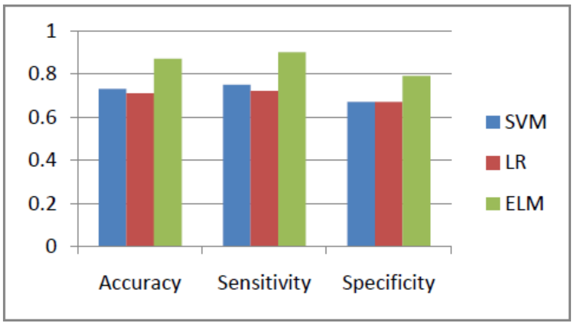

Fig.5. Visual Representation of performance measures for different classification methods.

Performance measures for different classification methods are given in above table 2, where existing methods like SVM, LR and LDA are implemented and process is carried out on same DDSM dataset. Then obtained results are compared with proposed ELM method. It is found that ELM gives better accuracy compared to other methods.

V. CONCLUSION

In this paper, ELM method is proposed for classification. The performance measures are evaluated and obtained 0.87 accuracy, 0.90 sensitivity and 0.79 specificity. Other existing methods like SVM, LR and LDA are also implemented and comparison analysis is carried out. It is found that the proposed method gives better results than others.

REFERENCE

[1] Maini, Raman. and Aggarwal, Himanshu. A Comprehensive Review of Image Enhancement Technique, Journal Of Computing, 2010, Volume 2, Issue 3, Issn 2151-9617.

[2] Saini, Vinod and Gulati, Tarun. A Comparative Study on Image Enhancement Using Image Fusion. International Journal of Advanced Research in Computer Science and Software Engineering, 2012,Volume ss2, Issue 10.

[3] Pisano, Etta D., Shuquan Zong, Bradley M. Hemminger, Marla DeLuca, R. Eugene Johnston, Keith Muller, M. Patricia Braeuning, and Stephen M. Pizer. Contrast limited adaptive histogram equalization image processing to improve the detection of simulated spiculations in dense mammograms.Journal of Digital Imaging11, no. 4,1998: 193-200

[4] Wang, Chao, and Zhongfu Ye. Brightness preserving histogram equalization with maximum entropy: a variational perspective.Consumer Electronics, IEEE Transactions on51, no. 4,2005: 1326-1334.

[5] Abdullah-Al-Wadud, Mohammad, Md Hasanul Kabir., M. Ali Akber Dewan, and Oksam Chae. A dynamic histogram equalization for image contrast

enhancement.Consumer Electronics, IEEE Transactions on53,2007, no. 2: 593-600.

[6] Sundaram, M., K. Ramar, N. Arumugam, and G. Prabin Histogram based contrast enhancement for mammogram images. InSignal Processing, Communication, Computing and Networking Technologies (ICSCCN), International Conference on 2011, pp. 842-846. IEEE.

[7] Tomasi,C., R ManduchiBilateral filtering for gray and color images. Proceedings of the IEEE International Conference on Computer Vision, 1998, Bombay, India.

[8] M. RaviKumar, P G Rachana, B J Shivaprasad, D S Guru. Chapter 29 Enhancement of mammogram images using CLAHE and Bilateral Approaches", Springer Science and Business Media LLC. 2021.

[9] Gairola, Akhilesh Chandra., Owais Ahmad Shah. Design And Implementation Of Low Pass Butterworth Filter, IJCRT | Volume 6, Issue 2 April 2018 | ISSN: 2320-2882.

[10] Seddik. Hassen, Ezzedine Ben Braiek. Efficient Noise Removing based Optimized Smart Dynamic Gaussian Filter. International Journal of Computer Applications (0975 – 8887) , 2012, Volume 51– No.5.

[11] Sivaramakrishna, Radhika, Obuchowski, Nancy A., Chilcote, William A., Gilda, Cardenosa. and Powell, Kimerly A. Comparing the performance of mammographic enhancement algorithms: a preference study.American Journal of Roentgenology175,2000, no. 1: 45-51.

[12] Ko, Sung-Jea. Center weighted median filters and their applications to image enhancement. Circuits and Systems, IEEE Transactions on, 1991, 0098-4094, pp. 984 – 993.

[13] Görgel, Pelin & Sertbaş, Ahmet & Ucan, Osman. Mammographical mass detection and classification using Local Seed Region Growing-Spherical Wavelet Transform (LSRG-SWT) hybrid scheme. Computers in biology and medicine. 43. 765-74. 10.1016/j.compbiomed.2013.03.008.

[14] Shakeel, Sobia and Gulistan Raja. Classification of Breast Cancer from Mammogram images using Deep Convolution Neural Networks. International Bhurban Conference on Applied Sciences and Technologies (IBCAST) (2021): 595-599.

[15] Hariraj, Venketkumar & Khairunizam, Wan & Vijean, Vikneswaran & Ibrahim, Zunaidi & Abu bakar, Shahriman & Mohamad Razlan, Zuradzman & Thavasimuthu, Rajendran & Sathiyasheelan, R. Fuzzy multi-layer SVM classification of breast cancer mammogram images. International Journal of Mechanical Engineering and Technology. 9. 2018, 1281-1299.

[16] M. Thilagaraj, N. ArunKumar, Petchinathan Govindan, Classification of Breast Cancer by implementing improved DCNN with Artificial Fish School Model. Computational Intelligence and Neuroscience / 2022 . https://doi.org/10.1155/2022/6785707.

[17] Mahmood, T., Li, J., Pei, Y., Akhtar, F., Rehman, M. U., & Wasti, S. H. Breast lesions classifications of mammographic images using a deep convolutional neural network-based approach. PloS one, 2022,17(1), e0263126. https://doi.org/10.1371/journal.pone.0263126.

[18] K. T. Rajakeerthana, C. Velayutham, and K. Thangavel, Mammogram Image Classification Using Rough Neural Network, pp. 133–138, Springer India, 2014, New Delhi, India.

[19] W. Peng, R. V. Mayorga, and E. M. A. Hussein. An automated confirmatory system for analysis of mammograms, Computer Methods and Programs in Biomedicine,2016, vol. 125, pp. 134–144.

[20] H. Alharbi, G. Falzon, and P. Kwan, A novel feature reduction framework for digital mammogram image classification, in Proceedings of the 3rd IAPR Asian Conference on Pattern Recognition, ACPR 2015, pp. 221–225, Malaysia.

[21] Adoui, Mohammed El & Mahmoudi, Sidi & Larhmam, Amine & Benjelloun, Mohammed. MRI Breast Tumor Segmentation Using Different Encoder and Decoder CNN Architectures. 2019, Journal of Computers. 8. 52. 10.3390/computers8030052.