# An Optimized Mammogram Image classification Using Feed Forward Neural Networks

**C Senthilkumar[1], K Gayathri Devi[2], Kishore B[3], V R Vinothini[4]**
[1,2]Dr.N.G.P.Institute of technology, Coimbatore, India
[3]Dr.K.Mahalingam College of Engineering and Technology, Pollachi, India
[4]Bannari Amman Institute of Technology, Sathy,India
Corresponding Author : senthilkumar02@gmail.com

**Abstract** - Breast cancer is a life-threatening condition in which cancer cells grow in the breast tissues. Though mammograms are the most effective screening tools, they aren't always accurate in detecting malignancies at an early stage. Early detection is the most effective strategy to increase the chances of survival and to treat diseases as effectively as possible. The goal of this effort is to determine if breast cancer is benign or malignant and in an early stage. Pre-processing, segmentation, classification, and cancer stage detection are the primary steps. Pre-processing of mammogram pictures improves picture quality and decreases noise. GLCM approaches, which leverage four key qualities, are used to extract key characteristics from pre-processed pictures. To adjust the shape of the tumor boundaries, some morphological operations are performed. Clustering with the help of DWT is used to reduce the size of the image. The tumor stage will be determined by the final results.

**Key words:** Tumor, Mammogram image, Cuckoo Search Algorithm, Discrete wavelet Transform, Gray level Co-occurrence matrix, Early Detection
**DOI Number: 10.48047/nq.2022.20.19.NQ99045** **NeuroQuantology2022; 20(19):484-493**

## 1 Introduction

Cancer is the second leading cause of mortality in children under the age of eight. Cancer claimed the lives of 8 million people. Breast cancers [19,20] in the ducts, the parts of the breast where milk passes, are called ductal breast cancers. Inflammatory breast cancer develops on the inside of the breast's pores and skin. Breast cancer is the second leading cause of death among women around the world. In 2019, women in the United States are predicted to be diagnosed with 268,600 new cases of invasive breast cancer and 62,930 new cases of non-invasive breast cancer. Early detection [16,17,24] is the most effective strategy to maximize the likelihood of successful treatment and long-term survival. In marketing, social science, finance, and medical, data mining has become the most effective technique for knowledge discovery. This paper is organized to have four sections. The literature and existing works are presented in Section 2. In Section 3, the proposed methodology has elaborated. The results and discussions are presented in Section 4. The results presented are proved to be accurate and efficient when compared to other models.

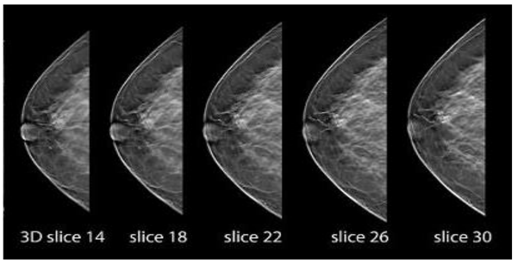



Fig. 1. Mammogram Image

## 2 Related works

The literature review of existing systems is detailed in this chapter. It deals with the discovery of breast cancer, as well as the stages of the disease and the actions done in response to them. This has aided in gathering information about the present systems' operations and procedures, which has aided in the project's modification. Finally, 10 fold cross-validations were used, and tests were run on three different classifiers.

Naive Bayes[1,4,5] proposes a training support vector classifiers, the SMO model uses John Platter's sequential minimal optimization approach. This approach fills all missing values globally and converts nominal characteristics to binary attributes. By default, all attributes are normalized. To evaluate all of the classifiers in this work, we used five performance measures: true positive, false positive, ROC curve[2,23], standard deviation (STD), and accuracy (AC)[7,11,12].

RNNs are the group of Neural Network (NN) that are deep in sequential dimension and were exploited widely in time sequence modelling. In contrast to a traditional NN, RNNs are capable of processing the data points where the activation at every step is based on prior step.

CNN exploits the spatial data [3,13,15,17] amongst the image pixels and therefore, they depend on "discrete convolution". Accordingly, a gray scale image is presumed.

HA-BiRNN [9,18] comprises of two layers of encoder that are exploited for sentence encoder and word encoder, respectively. Along with this, sentence-level attention and word-level attention are also considered.

The authors have taken most popular BC detection methods namely; Naïve Bayes Classifier, Support Vector Machine (SVM) Classifier [22,23], Bi-clustering and Ada boost Techniques, R-CNN (Convolutional Neural Networks) Classifier, Bidirectional Recurrent Neural Networks (HA-BiRNN) [6–9,14]. These methods are described in this section. SVM Classifier technique [6,11,12] is an amalgamation of RFE and SVM.

## 3 Proposed Method

The breast cancer detection approach presented in this chapter is focused on the use of machine learning algorithms. Our system performs well in determining the stage of cancerous cells in the breast. Machine learning and MATLAB applications are used for pre- processing, clustering, and segmentation are shown in figure 2.

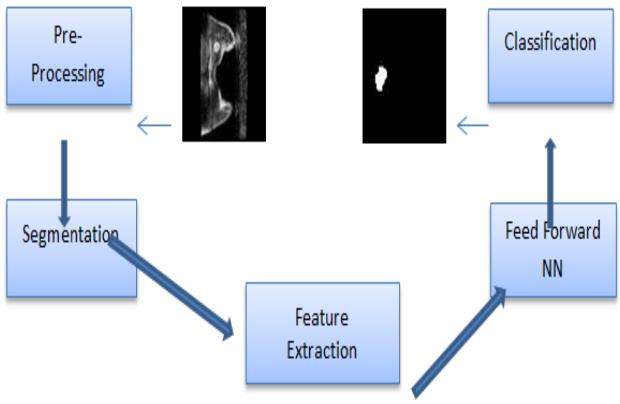



Fig. 2. Proposed Method

495

## 4 Experiments and results

### 4.1.1 Pre processing

Pre-processing is used to boost image data by suppressing undesirable distortions such as pectoral muscle suppression and breast border extraction, as well as enhancing certain image features. Since digital mammograms are medical images that are difficult to interpret, a preparation process is required to ensure reliable results.

### 4.1.2 Adaptive Median Filter

The Adaptive Median Filter uses spatial processing to figure out which pixels in an image are influenced by impulse noise. By comparing each pixel in the image to its neighbouring pixels, it classifies pixels as noise. The size of the neighbourhood and the reference threshold can also be changed. The median pixel value of the pixels in the neighbourhood that passed the noise labelling test is then used to replace the noise pixels.

### 4.1.3 Feature Extraction

Feature extraction is a technique for minimizing the amount of data to be processed while still accurately and completely representing the original data set by selecting or combining variables into features. The grey level co-occurrence matrix is used to extract features in this paper.

### 4.1.4 K-means Clustering

The K-Means Clustering is an unsupervised learning process which deals with finding a structure in a collection of unlabelled data. A cluster is a collection of objects which are related and unrelated to the objects fit into other clusters. The K-means clustering technique that groups N pixels of an image into K number of clusters, where K < n and K is a positive integer. The main drawback of 'K' is that the number of clusters must be computed and it does not yield the same result each time the algorithm is executed and the resulting clusters depend on the initial assignments of centroids.

### 4.1.5 Fuzzy C-Means Algorithm

Fuzzy clustering plays an important role in solving problems in the areas of pattern recognition and fuzzy model identification. To avoid the rapid convergence and always grouping into one cluster, one use before standardizing the weights over Q. Where $w_{max}$, $w_{min}$ are maximum or minimum weights over the weights of all feature vectors for the particular class prototype.

$$w[q,k] = (w[q,k] - w_{min})/(w_{max} - w_{min}) \quad (1)$$

After the fuzzy c-means iteration, for the purpose of comparison and to pick the optimal result, one adds Step 9 to calculate the cluster centres and the modified Xie-Beni clustering validity $\kappa$ :The Xie-Beni validity is a product of compactness and separation measures. The compactness-to-separation ratio $\nu$ is defined by Equation.

$$\nu = \{(1/K)\sum(k=1,K)\sigma k2\}/D_{min}2 \quad (2)$$

$$\sigma k2 = \sum(q=1,Q) \; wqk \; || \; x(q) - c(k) \; ||2$$

$D_{min}$ is the minimum distance between the cluster centres.

The variance of each cluster is calculated by summing over only the members of each cluster rather than over all Q for each cluster, which contrasts with the original Xie-Beni validity measure.

$$\sigma k2 = \sum\{q: q \text{ is in cluster } k\} \; wqk \; || \; x(q) - c(k) \; ||2 \quad (3)$$

The spatial function is included into membership function as given in Equation.

### 4.1.6 Cuckoo Search Optimization Algorithm (CSOA)

Cuckoo search is one of many nature-inspired algorithms used extensively to solve optimisation problems in different fields of engineering. The CS optimisation algorithm is basically based on the following three rules:

• Each cuckoo selects a nest randomly and lays one egg in it.

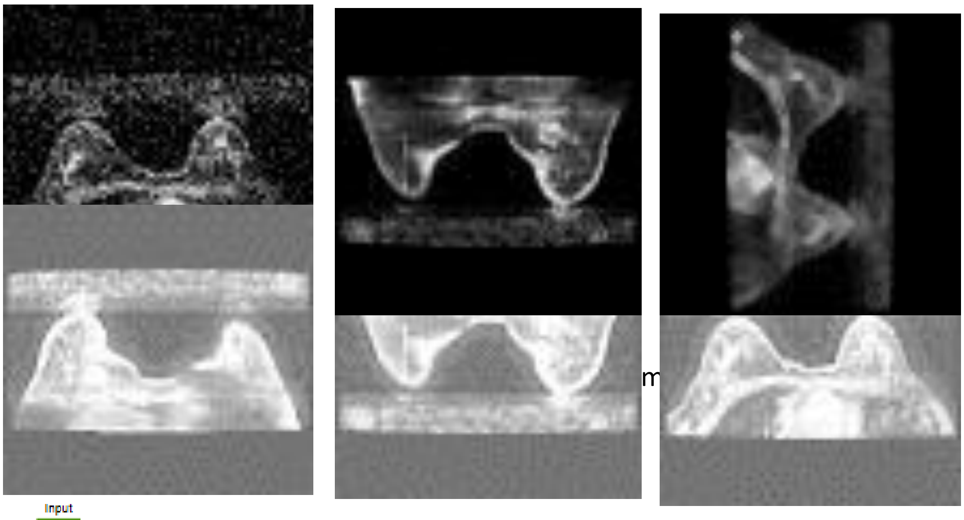
• The best nests with high quality of eggs will be carried over to the next generation

• For a fixed number of nests, a host cuckoo can discover a foreign egg with a probability ϵ [0,1]. In this case, the host cuckoo can either throw the egg away or abandon the nest and build a new one somewhere else.

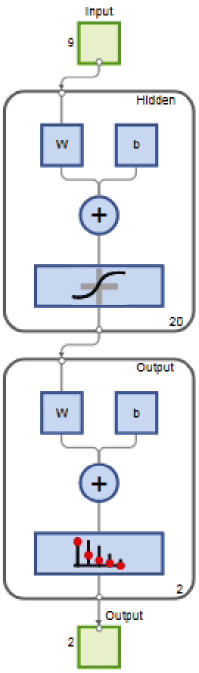
496

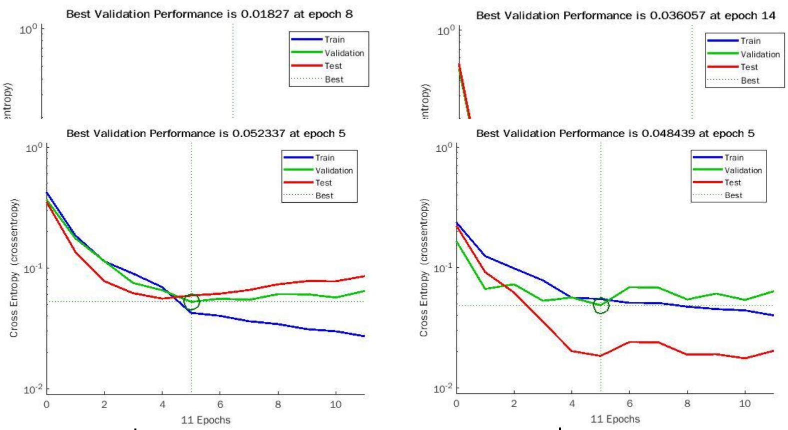
#### 4.1.7 Feed-Forward Neural Network (FFNN)

The feed-forward neural network is used in this research for the mammogram image classification and validation of results. The different sizes of hidden layers are used to classify the mammogram image. The input features selected for the network is nine and output image classification is two (Normal and abnormal). The test images of mammogram and results are given in figure 3. The feed-forward neural network structure and best validation performance as shown in figure 4.(a) and (b).



m




ed-

tial

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 20 | 30 | 10 | 20 | 30 | 10 | 20 | 30 |
| | 0 | 0 | 31 | 13 | 14 | 1000 | 1000 | 1000 |
| | - | - | 00:00:01 | 00:00:01 | 00:00:01 | - | - | - |
| | 0.465 | 1.61 | 0.0202 | 0.0247 | 0.0261 | 0 | 0 | 0 |
| Gradient 1.52 | 0.528 | 2.42 | 0.00851 | 0.01 | 0.00863 | 1e-06 | 1e-06 | 1e-06 |

497

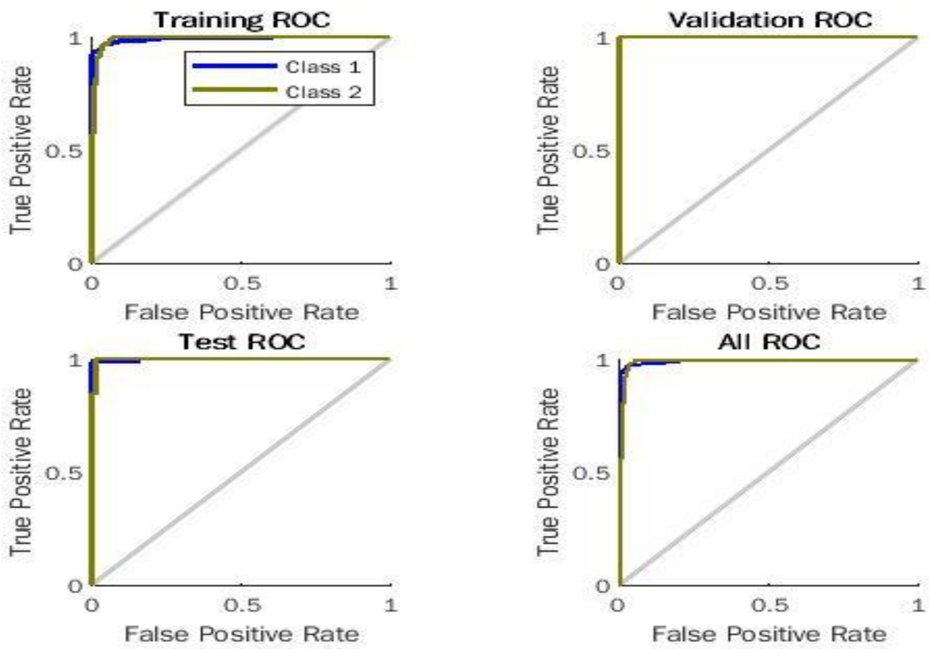



Fig.5. Validation of results



## 5 Conclusions

This system provides a solution for the detection of tumor at an early stage and it is an efficient method for identifying the tumor. The proposed system is highly practical values in realizing information and segmenting the tumor images. Digital mammogram image is taken as input. The Input Image is first deionized using Standard Median Filter. Then edges of the images are enhanced. Pre-Processing is used to convert RGB image to gray scale image, after this process Dual-Tree Complex Wavelet Transform is used to enhancement the discrete wavelet transforms and GLCM Matrix method is used with gray-level value I occur either horizontally, vertically, or diagonally to adjacent pixels with the value.

Table 2 Performance analysis of existing Breast Cancer methods

| Methodology | Accuracy | Precision | Recall |
|---|---|---|---|
| Naïve Bayes | 95.61 | 95.65 | 93.61 |
| Support Vector Machine | 95.61 | 95.65 | 93.61 |
| Bi-clustering and Ada boost model | 95.75 | 95.72 | 96.26 |
| Recurrent Convolutional Neural Networks(RCNN) | 91.3 | 91.3 | 89.3 |
| Bi-directional Recurrent Neural Networks(HA-BiRNN) | 85.20 | 80.09 | 79.03 |
| Deep Neural Network with Support Value(DNNS) | 97.21 | 97.9 | 97.01 |
| **Proposed Methodology** – Feed-forward Neural Network(FFNN) | **98.12** | **98.85** | **97.04** |

The image features such as energy, contrast, correlation, Homogeneity etc., to be extracted from the image. The different sizes of hidden layers are used to classify the mammogram image. The input features selected for the network is nine and output image classification is two (Normal and abnormal). The performance analysis of different breast cancer methods are compared with accuracy, precision and recall parameters. The proposed algorithm classifies the input image with an accuracy of 98.12 %. It is ensured that the proposed algorithm is advantageous in both performance, efficiency and quality of images are decisive in the modern medical systems.

**REFERENCES**

[1] Al-Asad, Jawad F., et al. "Frequency domain despeckling technique for medical ultrasound images." Journal of Electrical Engineering 72.4 (2021): 229-239.

[2] Aloyayri, A., & Krzyżak, A. (2020, October). Breast Cancer Classification from Histopathological Images Using Transfer Learning and Deep Neural Networks. In International Conference on Artificial Intelligence and Soft Computing (pp. 491-502). Springer, Cham.

[3] Beevi, K. S., Nair, M. S., & Bindu, G. R. (2017). A multi-classifier system for automatic mitosis detection in breast histopathology images using deep belief networks. IEEE Journal of translational engineering in health and medicine, 5, 1-11.

[4] Chen, G. Y. (2021). Multiscale filter-based hyperspectral image classification with PCA and SVM. Journal of Electrical Engineering, 72(1), 40-45.

[5] Elmoufidi, A., El Fahssi, K., Jai-Andaloussi, S., Sekkaki, A., Gwenole, Q., & Lamard, M. (2017). Anomaly classification in digital mammography based on multiple-instance Learning. IET Image Processing, 12(3), 320-328.

[6] Gajjar, B., Mewada, H., & Patani, A. (2021). Sparse coded spatial pyramid matching and multi-kernel integrated SVM for non-linear scene classification. Journal of Electrical Engineering, 72(6), 374-380.

[7] Gayathri Devi, K., Balasubramanian, K., Senthilkumar, C. et al. Accurate Prediction and Classification of Corn Leaf Disease Using Adaptive Moment Estimation Optimizer in Deep Learning Networks. J. Electr. Eng. Technol. (2022). https://doi.org/10.1007/s42835-022-01205-0

[8] Grzegorczyk, T. M., Meaney, P. M., Kaufman, P. A., & Paulsen, K. D. (2012). Fast 3-D tomographic microwave imaging for breast cancer detection. IEEE transactions on medical imaging, 31(8), 1584-1592.

[9] Hajiabadi, H., Babaiyan, V., Zabihzadeh, D., &Hajiabadi, M. (2020). Combination of loss functions for robust breast cancer prediction. Computers & Electrical Engineering, 84, 106624.

[10] Inan, M. S. K., Hasan, R., &Alam, F. I. (2021, January). A Hybrid Probabilistic Ensemble based Extreme Gradient Boosting Approach For Breast Cancer Diagnosis. In

2021 IEEE 11th Annual Computing and Communication Workshop and Conference (CCWC) (pp. 1029-1035). IEEE.

[11] Kamalakannan, J. (2021, January). The Comparative Study of Segmentation Strategies for Bio-inspired Models of Mammography Images. In 2021 International Conference on Computer Communication and Informatics (ICCCI) (pp. 1-6). IEEE.

[12] Kozegar, E., Soryani, M., Behnam, H., Salamati, M., & Tan, T. (2017). Mass segmentation in automated 3-D breast ultrasound using adaptive region growing and supervised edge-based deformable model. IEEE transactions on medical imaging, 37(4), 918-928.

[13] Naik, S., Doyle, S., Agner, S., Madabhushi, A., Feldman, M., & Tomaszewski, J. (2008, May). Automated gland and nuclei segmentation for grading of prostate and breast cancer histopathology. In 2008 5th IEEE International Symposium on Biomedical Imaging: From Nano to Macro (pp. 284-287). IEEE.

[14] Paul, A., & Mukherjee, D. P. (2015). Mitosis detection for invasive breast cancer grading in histopathological images. IEEE transactions on image processing, 24(11), 4041-4054.

[15] Sánchez-Cauce, R., Pérez-Martín, J., &Luque, M. (2021). Multi-input convolutional neural network for breast cancer detection using thermal images and clinical data. Computer Methods and Programs in Biomedicine, 204, 106045.

[16] Senthilkumar C., Gnanamurthy R.K. , Automated Brain Tumor Segmentation from MRI Images using Morphometric Algorithms, Current Signal Transduction Therapy 2020; 15(3)

[17] Shamrat, F. J. M., Raihan, M. A., Rahman, A. S., Mahmud, I., &Akter, R. (2020). An Analysis on Breast Disease Prediction Using Machine Learning Approaches. International Journal of Scientific & Technology Research, 9(02), 2450-2455.

[18] Spanhol, F. A., Oliveira, L. S., Petit jean, C., &Heutte, L. (2015). A dataset for breast cancer histopathological image classification. IEEE Transactions on Biomedical Engineering, 63(7), 1455-1462.

[19] Tan, Y. J., Sim, K. S., & Ting, F. F. (2017, November). Breast cancer detection using convolutional neural networks for mammogram imaging system. In 2017 International Conference on Robotics, Automation and Sciences (ICORAS) (pp. 1-5). IEEE.

[20] Tan, Y., Shi, Y., & Tuba, M. (2020). Data Mining and Big Data: 5th International

Conference, DMBD 2020, Belgrade, Serbia, July 14-20, 2020, Proceedings (Vol. 1234). Springer Nature.

[21] Tang, J., Rangayyan, R. M., Xu, J., El Naqa, I., & Yang, Y. (2009). Computer-aided detection and diagnosis of breast cancer with mammography: recent advances. IEEE transactions on information technology in biomedicine, 13(2), 236-251.

[22] Wadi, M. (2021). Fault detection in power grids based on improved supervised machine learning binary classification. Journal of Electrical Engineering, 72(5), 315-322.

[23] Wang, Z., Li, M., Wang, H., Jiang, H., Yao, Y., Zhang, H., &Xin, J. (2019). Breast cancer detection using extreme learning machine based on feature fusion with CNN deep features. IEEE Access, 7, 105146-105158.

[24] Senthilkumar, C., and R. K. Gnanamurthy. "A Fuzzy clustering based MRI brain image segmentation using back propagation neural networks." Cluster Computing 22.5 (2019): 12305-12312.