

Development of a Neural Network using MATLAB for the detection of Breast Cancer Using ART 1 Method

Poulmi Banerjee¹, Chintan Roy², Munmoon Chaki³, Jit Modak⁴

^{1,2,3,4} Assistant Professor, Electronics and Communication Engineering,
Regent Engineering and Research Foundation Group of Institutions,

Abstract

The primary purpose of the unsupervised learning model ART1 is to identify binary patterns. As shown in the following diagram, it consists of an attention subsystem, an orienting subsystem, a vigilance parameter, and a reset module. On the system, the alertness parameter has a significant impact. Vigilance increases the ability to recall specific details. It is the formal study of how to get over learning instability caused by a competitive learning model, which includes an overview of a precise theory termed adaptive resonance theory (ART). This formal study suggested that the instability problem might be significantly solved by using a particular type of top-down learning feedback and matching method. It was known that these code-stabilizing mechanisms shared features with top-down attention mechanisms, which had previously been identified through a study of relationships between cognitive and reinforcement systems. To put it another way, once the formal solution to the instability problem was recognized, it also became clear that no new, quantitative mechanism needed to be developed in order to achieve it. Pattern categorization is one of the fundamental challenges that neural nets can be trained to do. Every input vector in pattern difficulties is classified as either belonging to or not belonging to a specific class. We assumed that, in the case of the neural net technique, we had built up training patterns for which the right categorization was known. When analyzing a single class, the output unit in the simplest instance indicates membership in the class with a response of 1; a response of 0 indicates that the pattern is not a member of the class. The ART 1 network used this classification technique.

Keywords: ART 1 network, Pattern categorization, Training Patterns, Vector

1. Introduction

1. Nowadays, cancer, or carcinoma, is a quite common disease. According to Dr. Mary Ling's (Breast & General Surgeon) webpage, the breast's milk-producing portion is separated into 15–20 portions known as lobes. The network of tiny tubes known as the ducts is where milk eventually exits the surface of the breast nipples. The dark patch of skin surrounding the nipple region is called the areola. Ligaments and connective tissues are key components in giving the breast its form. The sensation is produced by the

nerves in the breast. According to Ann Pietrangelo's information on the Health line website, the early warning signs and symptoms of breast cancer include

2. The symptoms include: (a) the appearance of a new lump in the breast or armpit; (b) breast swelling in certain areas; (c) rashes and irritation in the nipple area; (d) breast pain in any area; (e) changes in the size and shape of the breast; and (f) the discharge of fluid from the nipple other than breast milk.

A breast lump could be the result of aberrant cell division. Generally speaking, there are two kinds of breast tumors or masses:

Benign tumors: The National Breast Cancer Foundation INC states that when a tumor is determined not to be spreading, doctors typically leave it in place instead of making an effort to remove it. Even though these tumors don't usually pose a threat to the surrounding tissue, they can occasionally spread that way. When this happens and the patient experiences discomfort or other consequences, the tumor is removed..

Malignant tumors: Because they penetrate and harm the surrounding tissues, malignant tumors are cancerous and potentially hazardous. The National Breast Cancer Foundation INC states that a biopsy should be done to determine the extent of a malignant tumor when one is discovered. Cancerous cells proliferate in the human body when the proto oncogene is activated and transformed into an oncogene. The transition from proto-oncogene to oncogene is caused by a variety of factors, including genetics and environmental pollution-induced gene mutation^[6].

3. We are use ART1 network to find the breast cancer from some sample data and check the accuracy of the work for that need to design a ART 1 network through some phases that comprise the main operation of ART 1 categorization are as follows: –

a. Phase of recognition: Each node in the output layer presents a classification, which is compared with the input vector. If the neuron's output best matches the applied categorization, it becomes "1"; if not, it becomes "0."

b. Phase of comparison: In this stage, the input vector and the comparison layer vector are compared. The degree of similarity must be smaller than the vigilance parameter in order for the reset to occur.

c. Phase of search: During this stage, the network looks for resets and matches made during the previous phases. Therefore, the classification process is over if there is no reset and the match is good. If not, the procedure would have to be repeated in order to identify the correct match, requiring the sending of the other stored pattern.

2. Architecture

It is divided into the next two units:

Computational Unit: It consists of the following components: Input unit (F1 layer) – It also includes the next two parts:

The input component of the F1a layer in ART1 would merely contain the input vectors and not undergo any processing. It is linked to the interface section of the F1b layer.

The F1b layer interface portion is where the signal from the input portion and the F2 layer signal are combined. Bottom up weights (b_{ij}) connect the F1b layer to the F2 layer, whereas top down weights (t_{ji}) connect the F2 layer to the F1b layer.

The competitive layer is called the Cluster Unit (F2 layer). To learn the input pattern, the unit with the largest net input is chosen. All other cluster units have their activation set to 0.

Mechanism for Reset - This mechanism operates by comparing the input vector and the top-down weight. Consequently, a reset would occur if the degree of similarity was less than the vigilance parameter, which would prevent the cluster from learning the pattern.

layer is connected by bottom up weights (b_{ij}) to the F2 layer, while top down weights (t_{ji}) connects the F2 layer to the F1b layer.

Supplement Unit – The real problem with the reset mechanism is that layer F2 needs to be available while learning occurs and needs to be suppressed under specific circumstances. This is the reason why the reset unit, R, and two supplementary units, G1 and G2, are included. We refer to them as gain control units. These units communicate with other units in the network by sending and receiving signals. An excitatory signal is denoted by '+', and an inhibitory signal is shown by '-' (Fig.1).

3. Literature Review

- According to (S.Vijaya1, Dr. D. Gladi, et.al. 2018), Cancer is one of the most common diseases that destroy humans. Among them, genetics, diet, environment, way of life, etc., are contributing factors to breast cancer, which is more prevalent in women. This study project offers information about cutting-edge techniques. These days, the majority of disease diagnosis in the medical field uses neural networks. The data has gone through pre-processing steps such as scaling, normalization, and replacement of missing values. The preprocessed data has gone through several phases, including categorization, training, and assessment using several performance metrics. The ART1 neural network approach is used in this study's breast cancer classification with enhanced F-Score feature reduction, and the outcomes provide support for the computation of several performance indicators. According to this study, breast cancer should be classified as Benign and Malignant, as well as to compute and evaluate the suggested neural network approach's performance metrics using a feature dataset^[1].
- According to (Jieun Koh, et. al. 2018) the AJCC committee classified lobular carcinoma in situ as a benign entity and excluded it from the in situ carcinoma (pTis) category. The nipple-related disorders DCIS and Paget are now classified as Tis (DCIS) and Tis (Paget disease) instead of being in the same category as parenchymal carcinoma. Based on the extent of the invasive components, the invasive carcinoma is now classified as T1-3 without the need for loco region intervention. The greatest invasive tumor size is considered for staging purposes when estimating the tumor's volume.. The eighth version, which was released by the AJCC committee, clarifies that the maximum diameter of the biggest tumor should be determined without taking into account the tumor's tiny satellite foci. During the imaging procedure, it's important to remember that the size of any micro calcifications or architectural distortions that are connected to the main tumor should also be taken into account when measuring the largest tumor. T1 tumors are classified into four subcategories based on their dimensions: T1mi (tumors with dimensions $\leq 1\text{mm}$), T1a (tumors with dimensions in the range 1mm–5mm), T1b (tumors with dimensions in the range 5mm–10mm), and T1c (tumors with dimensions in the range 10mm–20mm). The next category is T2, whose dimensions fall between 20 and 50 mm, and T3, whose dimensions fall between 50 and greater mm. When there is a chance that the skin or the chest wall may be invaded by breast malignant cells, the tumor is placed in the T4 category, which is the final one^[3].

- According to (Lilian C. Wang, et.al., 2013) a linear array transducer operating at either 17-5 or 12-5 MHz was used to perform the US assessment. A needle with a gauge of 12 or 14 was needed, which was actuated by a spring-loaded biopsy mechanism. Imaging in the radial plane aids in the assessment of anomalies in the ductal part, whereas imaging in the anti radial plane aids in the investigation of margins. Harmonic image processing is useful in identifying isoechoic lesions when setting non-calcified DCIS. These lesions are especially common in patients whose fatty breast parenchyma has been discovered. At mammography, the increased breast density could be hidden behind the intrusive part. The results of the breast ultrasound scan indicate that the calcification is not as noticeable as it is on mammography. The ultrasound of calcification can also be used as a guide for a possible biopsy. This technique has the advantage of not requiring ionizing radiation and has proven to be less expensive than stereotactic biopsy^[2].
- According to (Adam Mracko, et.al., 2023) The use of deep neural networks in mammography is becoming more common. Since training algorithms need a lot of data to capture the overall relationship between the model's input and output, data are essential to the training of these models. The most readily available source of mammogram data for neural network training is open-access databases. Our approach primarily consists of a thorough survey of mammography datasets containing designated anomalous areas of interest in pictures. Databases include INbreast, the OPTIMAM Medical Image Database (OMI-DB), the Curate Breast Imaging Subset of Digital Database for Screening Mammography (CBIS-DDSM), and The Mammographic Image Analysis Society Digital Mammogram Database (MIAS) are included in the survey. We also reviewed previous research that have used these databases in conjunction with neural networks and the outcomes that have been obtained. At least 3801 unique photos with 4125 descriptive findings from roughly 1842 patients can be obtained from these databases. Approximately 14,474 people have significant discoveries; this number can vary based on the nature of the agreement with the OPTIMAM team. In order to improve comprehension of the data derived from these datasets, we also offer an explanation of the annotation procedure for mammography pictures^[4].
- According to (Mohammed Amine Naji, et.al., 2021) the number of deaths from breast cancer is rising dramatically every year. It is the most common kind of cancer overall and the leading cause of death for women globally. Any advancement in the identification and prognosis of cancer is crucial to a long and healthy life. Therefore, it's critical to have a high level of accuracy in cancer prognosis in order to update patient survivability standards and treatment aspects. Machine learning approaches have shown to be a powerful method, have become a research hotspot, and can significantly contribute to the process of early detection and prediction of breast cancer. Using the Breast Cancer Wisconsin Diagnostic dataset, we ran five machine learning algorithms in this study: Support Vector Machine (SVM), Random Forest, Logistic Regression, Decision tree (C4.5), and K-Nearest Neighbors (KNN). Once the results were in, we compared and evaluated the performance of each classifier. This study paper's primary goal is to identify the most efficient machine-learning algorithms in terms of confusion matrix, accuracy, and precision for the detection and prediction of breast cancer. The Support Vector Machine is shown to have attained the maximum accuracy of 97.2%, outperforming all other classifiers^[5]

4. Proposed Work

Taking A database as a reference from “Prof. Dr. Rüdiger Schulz-Wendtland Original owners of database” which specifies that the BIRADS evaluation of mammography’s where we get

Benign: 516

Malignant: 445

Attributes: 6

Number of Instances: 961

Taking 4 attributes as a input vector and 1 attribute as a output vector. Patient age is not considered as a input. Taking Shape, Density, Margin and BIRADS assessment as a input and Types of tumor as output. Converting the data into binary form and use this dataset as training and testing purpose. Create a ART1 network through MATLAB software and uses this database.

First collect the raw data from then convert the data into binary form and also delete some discrepant data which are not relevant with our work. After conversion a network should be create in MATLAB using MATLAB code, pass the data which are present in a excel format and call the data as the purpose of training and testing. We use Vigilance Parameter in a form of accuracy of the test result. The main advantage of ART 1 network that exhibits stability and is not impacted by a variety of inputs supplied to it(Fig.2).

For output measurement:-

0000= Benign Tumor

0001=Malignant Tumor

For Input measurement:-

Input1) The outcomes and observations of breast imaging on mammography, ultrasound, and MRI are described by the Breast Imaging Reporting and Data System (BI-RADS).

BI-RADS 0 (incomplete): Recommend additional imaging — mammogram or targeted ultrasound

BI-RADS 1 (negative): Routine breast MR screening if cumulative lifetime risk $\geq 20\%$

BI-RADS 2 (benign): Routine breast MR screening if cumulative lifetime risk $\geq 20\%$

BI-RADS 3 (probably benign): Short-interval (6-month) follow-up

BI-RADS 4 (suspicious): Tissue diagnosis

BI-RADS 5 (highly suggestive of malignancy): Tissue diagnosis

BI-RADS 6 (known biopsy-proven malignancy): Surgical excision when clinically appropriate.^[8]

BI-RADS 0= 0000

BI-RADS 1= 0001

BI-RADS 2= 0010

BI-RADS 3= 0011

BI-RADS 4= 0100

BI-RADS 5= 0101

BI-RADS 6= 0110

Input2) Shape (Mass shape, categorical):

round=0001

oval=0010

lobular=0011

irregular=0100

Input3) Margin: mass margin (categorical):

circumscribed=0001

microlobulated=0010

obscured=0011

ill-defined=0100

spiculated=0101

Input4) Density: mass density (ordinal)

High=0001

Iso=0010

Low=0011

Fat-containing=0100

5. Results

Training Outcomes: The ART1 network was trained using the preprocessed dataset. Throughout the training process, the network effectively updated its weights and created clusters based on the input patterns. After completing 1000 iterations, the network was able to successfully differentiate between two categories: benign and malignant tumors. The training phase culminated in the stabilization of the weight matrix and the finalization of cluster assignments.

Testing and Evaluation: A separate test set was used to assess the performance of the ART1 network. The network's predicted outputs were compared with the actual tumor labels (benign or malignant). The ART1 model attained an accuracy, more than **92.5%**, demonstrating that it correctly identified the tumor type in most test cases. This high accuracy reflects the network's effectiveness in distinguishing between benign and malignant tumors.

6. Conclusion

The model effectively classified tumors as benign or malignant using the selected imaging features, demonstrating the strength of the ART1 network in medical diagnostic applications. Its high accuracy highlights its potential for supporting clinical decision-making. Future studies could enhance this work by incorporating larger datasets, integrating additional relevant features, or exploring alternative neural network architectures to further improve diagnostic performance.

7. Figures

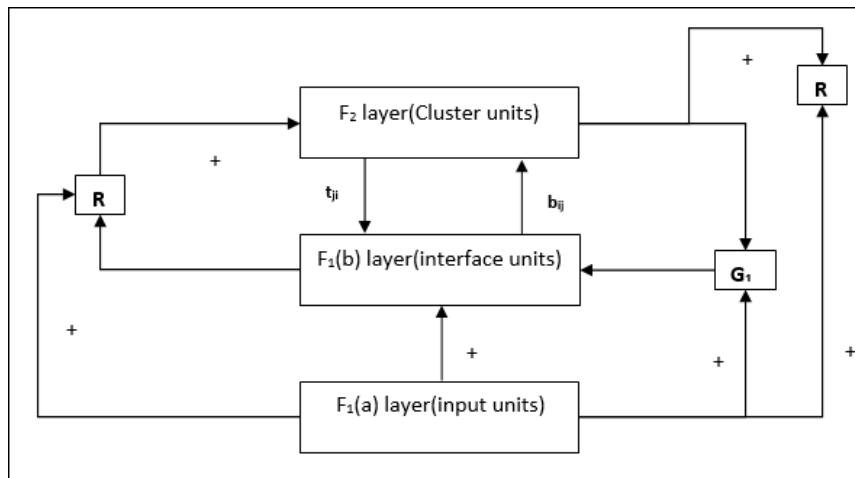


Fig.1 Functional Layers of ART 1 Network^[7]

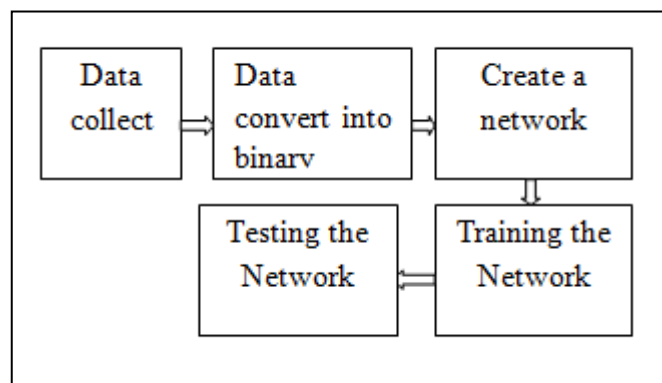


Fig.2 Block Diagram of the work

8. Appendix

Parameters Use

Following parameters are used –

- **n** – Number of components in the input vector
- **m** – Maximum number of clusters that can be formed
- **b_{ij}** – Weight from F_1b to F_2 layer, i.e. bottom-up weights
- **t_{ji}** – Weight from F_2 to F_1b layer, i.e. top-down weights
- **ρ** – Vigilance parameter
- **$\|x\|$** – Norm of vector x .

9. Authors' Biography

We would like to express our sincere gratitude to all those who contributed to the successful completion of this research work. Special thanks are extended to the faculty members of the Department of electronics and Communication Engineering, Regent Education and Research Foundation Group of Institutions, for their valuable guidance, encouragement, and constructive suggestions throughout the fulfillment of the work. The authors also acknowledge the support provided by for granting access to the necessary computational facilities and MATLAB resources required for the development and implementation of the neural network model. Finally, the authors are grateful to all researchers whose previous work in the field of neural networks and medical diagnosis laid the foundation for this study.

References

1. S.Vijaya , Dr D. Gladis. (International Journal of Pure and Applied Mathematics(2018)Volume 119 No. 16 2018, 365-381) Breast Cancer classification using ART1 neural network with Improved F-Score feature reduction.
2. Lilian C. Wang , Megan Sullivan, Hongyan Du, Marina I. Feldman, Ellen B. Mendelson(2013). US Appearance of Ductal Carcinoma in Situ. RadioGraphics, Vol. 33,No. 1.
3. Choudhary, T., et al. (2019). Breast mass classification using machine learning techniques. International Journal of Computer Applications, 182(46).
4. Elmore, J. G., et al. (2015). Variability in interpretive performance of screening mammography and radiologists' use of BI-RADS. Annals of Internal Medicine, 162(10), 673–681.
5. Mudigonda, N. R., Rangayyan, R. M., & Desautels, J. E. (2000). Gradient and texture analysis for the classification of mammographic masses. IEEE Transactions on Medical Imaging, 19(10), 1032–1043.
6. Carpenter, G. A., Grossberg, S., & Rosen, D. B. (1991). ART 2-A: An adaptive resonance algorithm for rapid category learning. Neural Networks, 4(4), 493–504.
7. Abdel-Zaher, A. M., & Eldeib, A. M. (2016). Breast cancer classification using deep belief networks. Expert Systems with Applications, 46, 139–144.
8. Carpenter, G. A., & Grossberg, S. (1987). ART 1: Self-organization and pattern recognition with a stability–plasticity tradeoff. Biological Cybernetics, 56(2–3), 77–93.
9. Jiang, Y., et al. (2007). Breast cancer diagnosis with neural networks. Cancer Letters, 245(1–2), 90–98.
10. Jieun Koh, MD and Min Jung Kim, MD, PhD(2018); Introduction of a New Staging System of Breast Cancer for Radiologists: An Emphasis on the Prognostic Stage.
11. Adam Mracko , Lucia Vanov canová and Ivan Cimrák (Journal of Imaging(2023)) .Mammography Datasets for Neural Networks—Survey
12. Mohammed Amine Naji , Sanaa El Filali , Kawtar Aarika , EL Habib Benlahmar , Rachida Ait Abdelouhahid , Olivier Debauche(Procedia Computer Science Volume 191, 2021, Pages 487-492). Machine Learning Algorithms For Breast Cancer Prediction And Diagnosis
13. Yap, M. H., et al. (2018). Automated breast ultrasound lesions detection using convolutional neural networks. IEEE Journal of Biomedical and Health Informatics, 22(4), 1218–1226.
14. American cancer society(2019).Newer and Experimental Breast Imaging Tests
15. https://www.tutorialspoint.com/artificial_neural_network/artificial_neural_network_adaptive_resonance_theory.htm
16. <https://radiology.ucsf.edu/blog/bi-rads-and-breast-mr-how-well-are-we-managing-patients-based-established-standards>