Comprehensive Journal of Science
Volume (10), Issue (37), (NOV. 2025)
SICST2025, www.sicst.ly
ISSN: 3014-6266

مجلة العلوم الشاملة
عدد خاص بالمؤتمر الدولي الثالث للعلوم والتقنية
المجلد (10)، العدد (37)، (نوفمبر2025)
ردمد: 3014-6266

Diagnoses Breast Cancer Disease by Using fuzzy artmap

1st ali Yahyai Alfakhi
Department of system analysis and programmer
institute of sciences technology, wadai alajal, Libya
Ali.almadany1977@gmail.com

2nd Mahmoud Ali Salah Alameri
Department of information technology
institute of engineering technology, sebha, Libya
mahmoud261320@gmail.com

Received: 30-09-2025; Revised: 10-10-2025; Accepted: 31-10-2025; Published: 25-11-2025

Abstract— This research concentrated on creating a fuzzy ARTMAP classifier to categorize breast cancer instances. The fuzzy ARTMAP is a neural network family, a component of artificial intelligence structures designed for continuous supervised learning of recognition classes. Deriving knowledge and insights from datasets, meaning data mining, has gained considerable interest within the database sphere to forecast emerging data patterns for undiagnosed patient conditions. This paper introduces a method for diagnosing breast cancer illness using an algorithm encompassing several facets of actual data. Thus, this setup aids pathologists when addressing disease diagnosis, particularly where certain signs of this cancer are not readily apparent. The algorithm offers the chance to utilize trained and tested historical data to construct a framework. The software's outcome proves accurate for analysts to support them in clinical decision-making tools.

Keyword fuzzy artmap, epoch, supervised learning, missing value.

I. Introduction

The program was created utilizing a dataset and an algorithm known as Fuzzy Artmap (Adaptive Resonance Theory) to identify illness. "ART" is an unsupervised neural network that can learn incrementally and continually without forgetting what it has already learnt. It is a crucial part of the fuzzy artmap. A cognitive and neurological hypothesis on how the brain grows and learns to identify and remember things and experiences throughout life is called adaptive resonance theory.

In addition to explaining numerous facts about perception, cognition, learning memor y, and consciousness along the way, ART demonstrates how processes of learning, ca tegorization, expectation, attention, resonance, synchronization, and memory search i nteract to allow the brain to learn quickly and

memories steadily. The AI and database fields have recently focused on learning and discovery from databases a lot of attention. The feed-forward Artificial Neural Network (ANN) has various uses, including classification. One method used in data mining is ANN. Supervised neural networks and fuzzy artmaps are two types of neural networks used in artificial neural networks (ANNs) that are used to train and evaluate models based on historical data. We shall explain the Fuzzy ARTMAP neural network topologies before giving our primary findings. Next, we will demonstrate how universal function approximation may be supported by a fuzzy ART neural network that has been augmented with layers of perceptions. We will next demonstrate how Fuzzy ARTMAP can enable this similar functionality on its own. Lastly, the usefulness of Fuzzy ART, the curse of dimensionality, and useful learning techniques will be covered.

II. Data Pre-Processing

It is challenging to find patterns in any data that has missing values, thus we employe d a data processing technique that may address this issue.In order to extract valuable i nformation from data that contains a variety of missing values, we replaced the missi ng value in our data with 1.

III. Fuzzy Artmap

Fuzzy ARTMAP comprises two Fuzzy ART neural network units linked via a MAP field, as seen in Fig1. During instruction, the tuple (z,y) is preprocessed to establish with a singular A-side and B-side. The pair ((z z),(y y)) which is supplied to the neural network. The instance z is given to the A-side Fuzzy ART unit (ARTA) and label y is supplied to the B-side Fuzzy ART unit (ARTB). Fuzzy ARTMAP conducts guided learning by mandating that the A-side FZ node which learns z will solely be associate.

A vague input pattern is an m-dimensional fuzzy vector denoted by z = (z1,z2………zn) Represent the m-dimension fuzzy input vector of the domain Fa1, and y = (y1,y,2………yn) denote n-dimensional fuzzy output Vector of the domain Fb2, each node in the domain possesses its own bottom-up fuzzy weight. Waj=(waj1,waj2……….wajn) and fuzzy weight wbj(wbj1,wbj2……wbjn) In the fuzzified ARTa, Waj mirrors ARTb wbj. Each element of a fuzzy vector is a fuzzy number. In the study here, for expediency, represent (z , y) to fuzzy artmap.

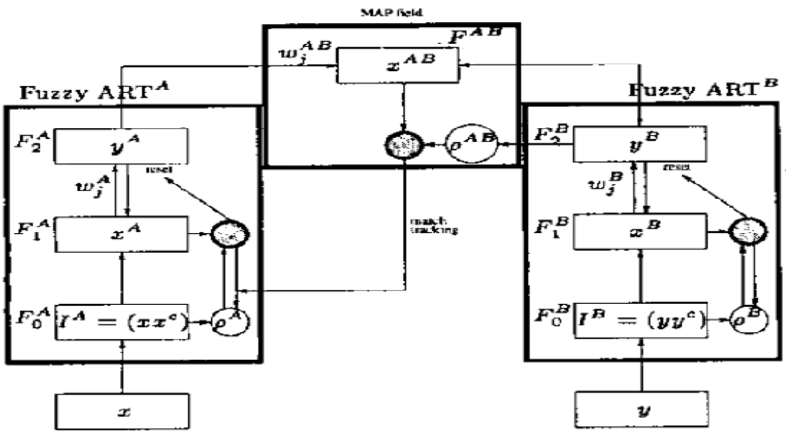

Fig. 1. The Fuzzy ARTMAP Architecture.

A. Complement Coding

Data scaling is vital. The weights are continually decreasing during training and learning since they are modified in this fashion, rendering it suitable and stable. As long as the neural network's FUZZY ARTMAP class is employed, Data normalization shows that each characteristic is bounded between 0 and 1. Complementary coding is below (1) from both the neural of the output vectors as Fg.2 and each neural of the templates.

The complement of the fuzzy value is

z=1-z ………..z is neural of the each input

y=1-y ……..y is the neural of the output

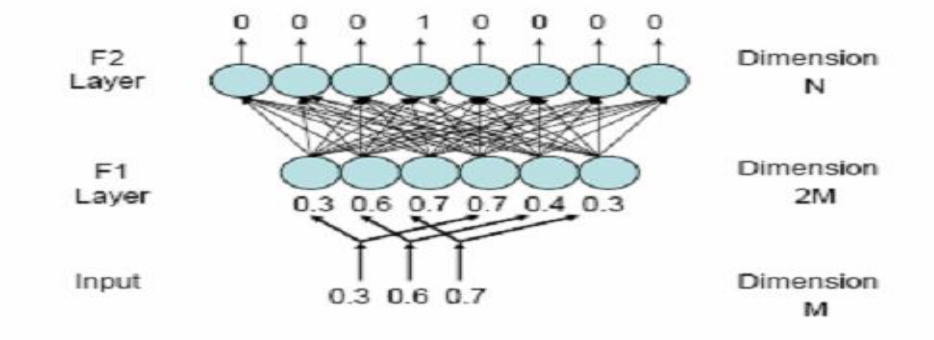

Fig 2. Complement Coding on each neural

B. Learning in FuzzyART

Every single F2 layer neuron's input weights are set to 1 when it is uncommitted. The network is shown the input vector that has been complement encoded. Subsequently, each neuron's function is assessed.

$$\mathrm{Y}n \equiv \sum_{1}^{n} \mathrm{Z} \wedge w \qquad \text{…….(1)}$$

Tj is computed for all the engaged Fa_2 neurons and the greatest such Tj is selected. Consequently, the system makes a category selection. If multiple Tj possess this peak value, the T with the minimal index j is picked. Fuzzy figures comprise the actual number from 0 to 1 the fuzzy and function, where

$$Z \wedge W_i = \max(Z, w) \qquad or \ \ if \ \ Z \ \ and \ \ W \ \ are \ \ vectors$$

$$(Z \wedge W) \equiv \max(Z^i \wedge W^i)$$

The normal (distance) portion | . | is define as $|Z| = \sum_{i=1}^{M} Zi$ …….(2)

C. Fuzzy resonance and reset

The vigilance element ρa is employed to regulate the operation of ARTa. Each novel class necessitates that ρa be raised to compel the emergence of a different class, while reduced ρa levels allow for enhanced compression of the acquired information. In the fuzzified ART, a selected category satisfies the fuzzy vigilance standard "if."

$$\frac{\left|I_1 \wedge W_1^a\right|}{\left|I_1\right|} \geq P^a \qquad \text{……..(3)}$$

This condition is termed fuzzy resonance where pa is the alertness parameter between 0<=p<=1 Subsequent to the arrival of fuzzy resonance, fuzzy weight adjustment follows. The top-down fuzzy weight waj does not align with the fuzzy input vector if

$$\frac{\left|I_1 \wedge W_1^a\right|}{\left|I_1\right|} \leq P^a \qquad \text{…….(3)}$$

D. Fuzzy Weight Learning (update)

When T jth category node in the Fa2 field is chosen, the fuzzy weights are updated by

$$W_i^a = I_1 \wedge W_i^{a(old)} \qquad \text{…….(4)}$$

C. Fuzzy Match Tracking

Should the vague input and vague target be initially introduced, the fuzzed ARTa vigilance parameter Pa equals a baseline vigilance Pa. If ARTb fails to forecast the right output for ARTa, then ρa is augmented to compel a novel category's formation in ARTa. This procedure is termed match tracking. If the present winner node cannot satisfy the vigilance standard in Fb, i.e.,

$$\frac{\left|Y^{ab} \wedge W_i^{ab}\right|}{\left|Y^{ab}\right|} \prec p_{ab} \qquad \text{…….(5)}$$

Where pab is the target vigilance parameter, then fuzzy match tracking raises the fuzzified ART1 vigilance Pa same above the (4) equation to tracking continues until fuzzy resonance happens, i.e., match ratio and seeks a new winner node in the field.

$$\frac{\left|Y^{ab} \wedge W_i^{ab}\right|}{\left|Y^{ab}\right|} \geq p_{ab} \qquad \text{…….(6)}$$

Fuzzy matching is testing the system for its correctness in showing predicted suggestions; this test set was then employed to gauge the system's accuracy. The system exhibited 94.84 percent precision after the initial epoch. Of all the patterns utilized for assessment, the system succeeded in proposing 656 correct diagnoses and 43 instances were incorrectly classified. The procedure, within the association unit, of aligning the two categories and revising the association weights is comparable to that employed in the ARTa units and it relies upon ρab ρab establishes the standard to validate the alignment of the input and intended output patterns.

IV. Discussion

The outcome relies on Pab. The span of pab from 0.1 to 0.5 to ascertain the level of coarseness or fineness of category prototypes toward classification precision. The greatest level of accuracy is 94.84 % when the magnitude of Pab was 0.1. Through that scope, we observe the magnitude of the Pointe has the most effect.

Target vigilance factor Pap is fixed at one for many-to-one correlation. Once the Jth category unit in the Fa2 area is selected to link the fuzzy input design of the Fa area with the fuzzy goal design of the Fb area, the mapping fuzzy weights are refreshed by.

V. Evaluation

The assessment was carried out to ascertain the precision of the system. Nevertheless, the accuracy of the method employed for this purpose, the precision of the method was examined by taking one of the instances in the case repository as a trial example. If the outcome yields one hundred percent resemblance then it would imply tha the algorithm is solid.

$$Accuracy = \frac{Total \quad of \quad correctness}{Total \quad cases} \times 100$$

So long as the precision of the system equals the quantity of correct predictions divided by the total quantity of all instances, and multiplied by 100. Thus, the accuracy was computed based upon the count of precise recommendations offered by the system over the count of instances utilized for evaluation.

VI. Conclusion and result

The outcome was contingent on Pab. The spectrum of pab from 0.1 to 0.5 helps ascertain the level of coarseness or fineness of category prototypes affecting classification precision. The maximum level of accuracy reached 94.84% when the Pab measure was 0.1; throughout that extent, we observed the Pointe magnitude had the greatest influence. To evaluate the system's correctness in offering predictive suggestions, the test dataset was subsequently employed to gauge the system's precision. The system displayed 94.84 percent accuracy following the initial epoch. Of all the samples utilized for testing, the system successfully proposed 656 correct diagnoses, while 43 instances were incorrectly classified.

The folding outcome here signifies the breast cancer data are segmented into five sections after being randomly divided, with each section containing 140 instances and 139, respectively. The preceding steps investigating the fuzzy ARTMAP show its capability for classification, as well as determining the classification precision for each segment. To apply the fuzzy ARTMAP for data classification, certain settings must be adjusted; these settings include pa=0.2 to govern the behavior of ARTA and pab=0.5 for the category vigilance factor. Following this, training will be conducted for every segment group excluding one part; specifically, only four sections of the data will be selected for training, and the remaining part for evaluation and deployment of the fuzzy ARTMAP.

For example, we are choosing the initial one to five segments of information for instruction and execution assessment in the final segment. Thus, as you can observe in the table 1 we possess the initial trial precision. The foremost figure for the test precision in the Table I is 95.71. This figure suggests the categorization of the fuzzy artmap is quite elevated, and the degree of flawed classification is quite low. However, in the second figure for test precision we notice the categorization of the fuzzy artmap is 59.28. This arises referencing pattern types, for instance, data domed or data variation, hence the fuzzy artmap is unable to sort such prior instances. The third figure for test precision is 98.58. In this figure we note here too the figure is close to the first segment, meaning the initial trial precision. Furthermore, in the fourth test precision we note this figure is 92.14 nearly both the first as well as the third figure. Lastly, the test precision is 62.58. From this figure we note it is comparable or near the second figure but superior to it. So, from these reviews, we can state or deduce generally, the categorization precision of the fuzzy artmap exceeds 50% from every segment. Considering that, fuzzy artmap is certainly proficient at sorting Breast cancer information with substantial precision.

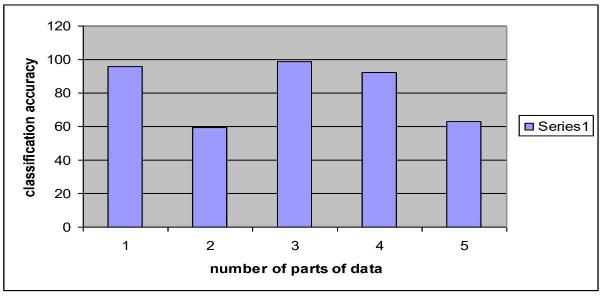

Fig 3. Chart of the above table.

Number	Test accuracy
1	95.71
2	59.28
3	98.57
4	92.14
5	62.85

Table I

Testing Accuracy for Corresponding Fold.

VII. Reference

[1] Liaw, L. C. M., Tan, S. C., Goh, P. Y., & Lim, C. P. (2024). Cervical cancer classification using sparse stacked autoencoder and fuzzy ARTMAP. Neural Computing and Applications, 36(22), 13895-13913.

[2] Mohanty, M. N., & Das, A. (2024). Skin cancer detection from dermatoscopic images using hybrid fuzzy ensemble learning model. International Journal of Fuzzy Systems, 26(1), 260-273.

[3] Das, A., & Mohanty, M. N. (2022). Design of ensemble recurrent model with stacked fuzzy ARTMAP for breast cancer detection. Applied Computing and Informatics.

[3] Abd Karim, S. A., Mohamad, U. H., & Nohuddin, P. N. E. (2025). Interaction-Based Feature Selection Technique Using Fuzzy Discretization and Class Association Rule Mining for Breast Cancer Classification. Malaysian Journal of Fundamental and Applied Sciences, 21(2), 1832-1859.

[3] Lai, W. C., & Srividhya, S. R. (2022). A modified LBP operator-based optimized fuzzy art map medical image retrieval system for disease diagnosis and prediction. Biomedicines, 10(10), 2438.

[3] Akalın, F., & Yumuşak, N. (2023). Classification of T-ALL, B-ALL and T-LL Malignancies Using Adaptive Network- Based Fuzzy Inference System Approach Combined with Nature-Inspired Optimization on Microarray Dataset. Afyon Kocatepe Üniversitesi Fen Ve Mühendislik Bilimleri Dergisi, 23(4), 941-954

[3] Abd Karim, S. A., Mohamad, U. H., & Nohuddin, P. N. E. (2025). Interaction-Based Feature Selection Technique Using Fuzzy Discretization and Class Association Rule Mining for Breast Cancer Classification. Malaysian Journal of Fundamental and Applied Sciences, 21(2), 1832-1859.

[4] Melton, N. M., da Silva, L. E. B., & Wunsch, D. C. (2025, March). An extensive analysis of match-tracking methods for ARTMAP. In 2025 IEEE Symposium on Computational Intelligence in Health and Medicine (CIHM) (pp. 1-8). IEEE.

[5] Yadav, A., Dwivedi, S., Dwivedi, A., Thakur, U., & Akhtar, D. N. (2025). Intelligent Disease Diagnosis: A Multi-Disease Prediction Approach Using Machine Learning. International Journal of Scientific Research in Science, Engineering and Technology (IJSRSET), Print ISSN, 2395-1990.

[6] Prusty, C. A. K., Patra, A., Ranjan, A. K., Kumar, R., & Das, A. (2025, January). Plant Disease Detection from Leaf

Images Utilizing Ensemble Convolutional Neural Network. In 2025 International Conference on Ambient Intelligence inHealth Care (ICAIHC) (pp. 1-6). IEEE.