

A Novel Diagnostic Computer Aided Medical Tool for Breast Cancer based on Neuro Fuzzy Logic

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ABSTRACT

Breast cancer is a second leading cause of cancer deaths worldwide and occurs in one of eight women. Diagnosis is a crucial step and is prerequisite for giving proper treatment. Medical diagnosis is a pattern classification dilemma to determine the disease. In this paper we present a novel medical diagnostic tool for the grading of BIRADS and its ability as a decision support system for radiologist. This tool is based on knowledge based intelligent computing system. The grading of BIRADS can be done by taking a set of characteristics like Mass Shape, Mass Margins, Mass density, Calcification and calcific distribution as input parameters. There is an ambiguity in categorization of multiple occurrences of BIRADS. BIRADS can be categorized accurately into BIRADS0 to BIRADS6 by taking each input parameter individually and making decision according to the single and multiple occurrences and both. This computer aided medical tool is a gifted tool to overcome the limitations of present day / current diagnostic system.

1. INTRODUCTION

1.1 Breast cancer

Cancer has been one of the biggest threats in human life and the leading cause of deaths over the next few decades. Deaths caused by cancer are expected to increase in future with an estimated 12 million people dying from cancer by 2030. Heart attack stands in the first position and followed by breast cancer as silent killers of women. As symptoms go widely unnoticed by the patient as well as health professionals, 1,06,124 number of Indian woman are predicted to be diagnosed with breast cancer by 2015. One of the key problem in treatment of cancer is the early detection of the disease.

Early diagnostic methods of cancer are an active area of the current research. The past History offered by the patient may be subjective, exaggerated, underestimated or incomplete. The measurements provided by the laboratory tests are often of limited precision and the exact borderline between normal and pathological measurements are often unclear. X-rays and mammogram and other similar procedures require correct interpretation of the results. Thus the state and symptoms of the patient known to the physician are limited and precise.

The present work aims to design and develop a novel diagnostic medical tool which focus on minute details required for early detection of breast cancer which is based on neurofuzzy logic.

1.2 Need for fuzzy logic in medical expert system The knowledge based expert system has been developed in the last decade for many medical applications by adopting artificial intelligence techniques. The knowledge based system in medical diagnosis was started in 70's and its usage actually stated in 80's. In the last decade the knowledge based system is embedding with other technologies like neurofuzzy, support vector machines.

1.3 Neural Networks: A neural Network is a machine that is designed to model the way in which the brain performs a particular task or function of interest with a massively parallel distributed processor made up of simple processing units. Multilayered feed forward networks, an important class of neural networks also known as multilayer perceptron which consists of a set of sensory units (source nodes) that constitute the input layer with one or more hidden layers and an output layer of computation nodes. The input signal propagates through the network in a forward direction on layer-by-layer basis. The hidden layer contains 7 hidden neurons $h_0, h_1, h_2, h_3, h_4, h_5, h_6$ that represent the symptoms of breast cancer. The output layer contains two neurons that produce the binary outputs.

2. Related work

2.1 Existing Medical expert Systems

The research paper of K.Ganesan given in overview discusses the recent advances and developments in the field of computer aided diagnosis of breast cancer using mammograms. Jansham Tang a senior member of IEEE he focused on key CAD Techniques developed for diagnosis of breast cancer including detection of calcifications, Masses architectural distortion bilateral asymmetry images enhancement and image retrieval. Jelena Bozek and Kathy J.Schilling's articles on Detection of Breast cancer to evaluate CAD performance with full field digital mammography. Maurice Samulski presented an interactive computer aided detection system reading mammograms. In his article "Computer aided detection mammography for breast cancer screening systematic review and meta-analysis".

"A computer aided Diagnosis system for Breast cancer using independent component analysis and Fuzzy Classifier" presented by Ikhlas Abdul khader and Fadi Abu -Amara the framework is based on combining principal component analysis (PCA) independent component analysis (ICA) and fuzzy classifier to identify and label suspicious regions. The article "An Evolutionary Neuro Fuzzy approach to breast cancer diagnosis" by R.E.Hamdi focus on TSK type fuzzy model is proposed to solve breast cancer diagnosis problem with a design combining the compact genetic algorithm and steady state genetic algorithm IEEE2010. Arpita Das's article "GA based Neuro Fuzzy techniques for Breast Cancer Identification" is an intelligent Computer Aided Diagnostic System may be developed to assist the radiologists to recognize the masses/lesions appearing in different groups of benign /malignancy . In this paper Genetic Algorithm has been used for searching significant input feature vectors and finally adaptive neurofuzzy based classifier. "An analysis of the methods employed for the Breast Cancer Diagnosis by Mahjabeen and Monika discuss about various techniques used for the diagnosis of breast cancer.

2.2 Mammography is the best available examination for the detection of early signs of breast cancer at present and it can reveal the pronounced evidence of abnormality such as masses and calcification. The advance in x-ray Mammography is digital mammography with which the breast images and captures in special electronic x-ray detector converts the image into digital picture for review on a computer monitor. An abnormal growth of tissues in the breast creates lumps or tumors in the breast. Mammography is capable of detecting such features that may indicate a potential clinical problem, which

include asymmetries between the breasts, architectural distortion, confluent densities associated with benign fibroses, calcifications and masses.

2.3 BIRADS: American college of Radiology Breast Reporting and Data System A breast mass is a localized sign of breast cancer and defined as a space-occupying lesion seen in at least two different projections. A mass may occur with or without associated calcifications. They may be circumscribed and spiculated masses. The common circumscribed mass is Fibroadenoma and usually found in younger age women. Spiculated lesions having stellate appearance on mammograms are high probability suspicious indicators of breast cancer.

(BIRADS) suggests a standardised method for Breast imaging and reporting. Mammography exams can be divided into two basic types for screening and Diagnostics. The standard screening examination includes two views of breast a Mediolateral oblique (MLO) and Craniocaudal (CC). The diagnostic Mammography is indicated when there are clinical findings such as palpable lump, localized pain nipple discharge and an abnormal screening mammogram.

2.4 The Mammography report:

The BIRADS standardized report includes four components.

1. The reason for the examination
2. The overall breast tissue composition
3. The description of the finding using standardized BIRADS terminology
4. The final assessment category which is linked by numeric category to the recommendation for management.
5. Reason for the examination
6. Example include "screening" "palpable mass" Additional workup of screening detected abnormality and 6-month follow up of a probably benign finding.
 - a. Breast tissue composition
7. The overall breast tissue composition can range from almost all fatty tissue dark gray to black on the mammogram to extremely dense tissue white on mammogram fatty tissue provides an excellent background in which helps to detect small cancers.
8. The four categories of breast tissue composition are a)almost entire fatty b) scattered islands of fibrogranular tissue c)Heterogeneously dense (which may lower sensitivity of mammography d)extremely dense(which lower and sensitivity of mammography).

Description of Findings

Normal benign suspicious findings are described using a standard lexicon. The description reflect common abnormalities such as the probability of malignancy masses and classifications.

2.5 Final Assessment

The BIRADS final assessment is current placed into seven categories each of which recommends a protocol.

BIRADS category incomplete need additional imaging evaluation reserved for screening exams that require additional workup before final assessment. Additional workup: additional workgroup additional mammography views or breast ultrasound.

BIRADS category 0: Reimaging.

BIRADS category 1: Negative. There is nothing to comment on

BIRADS category 2: Benign The examination is negative except for some typically benign findings.

BIRADS category 3: Probably Benign This is used for findings that have high probability of being benign(98%)

BIRADS category 4: Suspicious This includes abnormalities that donot have enough definite morphology of cancer but have enough concern to urge a biopsy.

BIRADS category 5: Highly suggestive malignancy.

These cases show classic findings of breast cancer (95%likelihood of malignancy). Assigning a BIRADS assessment category(0-6) to each mammography report provides a user-friendly mechanism for tracking and monitoring mammography patient that does not require the understanding of medical terminology.

3. Proposed work:

Occurrence relation between symptoms and diseases:

The references mention above are not able to grade the BIRADS using occurrence relation between symptoms and diseases. The fuzzy set of A of the symptom observed in the patient and fuzzy relation R representing the medical knowledge that relates the symptoms in the set S to the disease in set D, then the fuzzy B is possible diseases of the patients can be inferred by means of compositional rule of inference.

$$B=A \circ R$$

$$B(d)=\max\{(\min(A(s),R(s, d)))\}$$

For each $d \in D$

The symptoms observed in Fuzzy A represent the possibilities of the presence of severe symptoms of Breast cancer. The Membership grades the fuzzy set B denotes the possibility of attach in each relevant diagnostic label to the patient. The Fuzzy relation R of medical knowledge should constitute a greatest relation such that the fuzzy relation Q on the set P of patients and S symptoms and the fuzzy relation T on the sets P of patients and D of diseases then $T=Q \circ R$. Thus the relation Q and T represent the symptoms that are present and diagnoses consequently made for a number of known cases.

Fuzzy Sets and Fuzzy relation in medical diagnosis.

The uses of a fuzzy relation Q,T and R on Fuzzy sets A and B solve the fuzzy relation above equation for R to specify the relation between the symptoms and diseases.

Two types of relations can exist between symptoms and diseases, an occurrence relation and conformability relation.

1. The knowledge about tendency and frequency of appearance of a symptom when the specific disease present is provided by occurrence relation. The occurrence of symptom S with diseased.
2. The discriminating power of the symptom to confirm the presence of the disease is provided by conformability relation. The confirmation of a disease d by symptom S.

The difference between occurrence and conformability proves that a symptom that occur with a specific disease may also occur with several other diseases. This specifies that symptoms of a specific disease cannot be completely taken in to consideration for the confirmation of a disease.

On the other hand, a symptom may be rare but its existence can be considered to confirm the presence of a specific disease.

3.1 Pattern classification

Classification problems which are not linearly separable are called hard problems. The constraint of linear separability for pattern classification problems can be solved using a multilayer Feed Forward network with nonlinear processing units in all the intermediate hidden layers and in the output layer proposed.

Multilayer feed forward architecture could solve the representation of the hard problems in a network but leads to introduces the problem of hard learning. i.e the difficulty adjusting the weights of the network to capture the implied functional relationship between the given input-output pairs. The pattern mapping problems can be solves using back propogation algorithm.

Pattern Classification

Architecture: Two Layers, nonlinear processing units, geometrical interpretation

Learning: Preceptron learning

Recall: Direct

Limitation: Linearly separable function, cannot handle hard problems

To overcome: More layers lead to a hard learning problem

Pattern mapping or classification

Architecture: Multilayer Layers, nonlinear processing units, geometrical interpretation

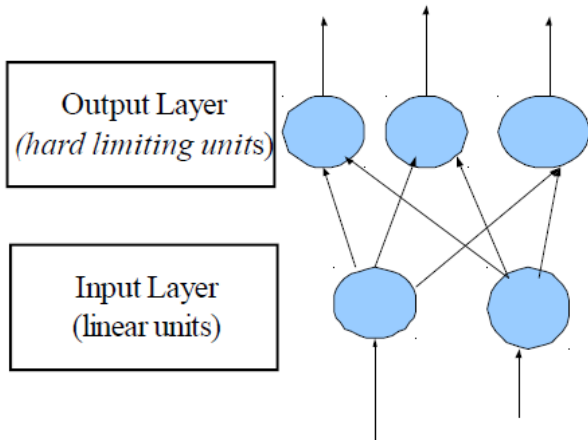
Learning: Generalized Delta Rule

Recall: Direct

Limitation: Linearly separable function, cannot handle hard problems

To overcome: More Complex architecture Geometrical interpretation of Hard Problems :Multilayer Perceptron

A pattern classification problem can be viewed as determining the hyper surfaces separating the multi dimensional patterns belonging to different classes. If the pattern classes are linearly separable then the hyper surfaces reduce to straight lines.



A two layer network consisting of two input units and N output units can produce N distinct lines in the pattern space. These lines can be used to separate different classes provided the regions are formed by the pattern classification problem are linearly separable.

If the output of the second layer are combined a set of units form by another layer then it can be shown that convex region can be formed by the separating surfaces.

A convex region is one which a line joining any two points is entirely confined to that region itself..It can be seen that the three-layer network decides the number of classes.

All the hard problems mentioned can be handled by multilayer perceptron.

1. Perceptron network

Weighted sum of input to a unit with handlimiting output function

2. Perceptron classification problem

For a two class (A1 and A2) problem determine the weights (w) and threshold(θ) Such that $WT - \theta > 0$ for a $\epsilon A1$ and $WT - \theta \leq 0$ for a $\epsilon A2$

3. Perceptron learning law

The weights are determined in an iterative manner using the following learning law at the (m+1)th iteration:

$W(m+1) = w(m) + \eta a(m)$, $WT(m) a(m) \leq 0$ and $a(m) \in A1 = w(m) - \eta a(m)$, $WT(m) a(m) > 0$ and $a(m) \in A2$

Where η is a d(positive) learning rate parameter

4. Perceptron learning as gradient descent

The perceptron learning law can be rewritten as a single equation

$W(m+1) = w(m) + \eta e(m) a(m)$, where $e(m) = b(m) - s(m)$ denoting

5. Perceptron convergence theorem

The perceptron learning law converges in a finite number of steps, provided that the given classification problem is representable.

6. Perceptron representation problem

A classification problem is representable by a single layer perceptron if the classes are linearly separable, separable by linear hyper planes in the input feature space. Classification problems that are not linearly separable are called hard problems

7. Multilayer perceptron

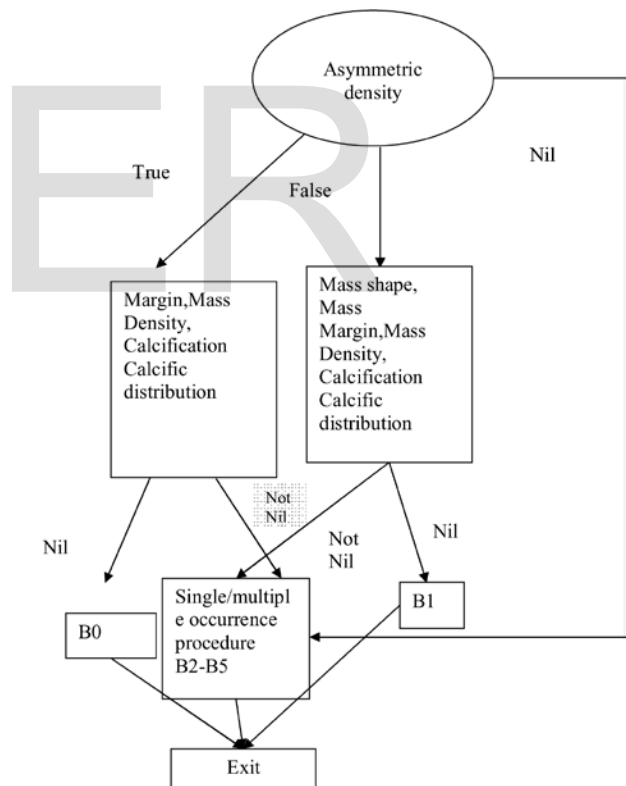
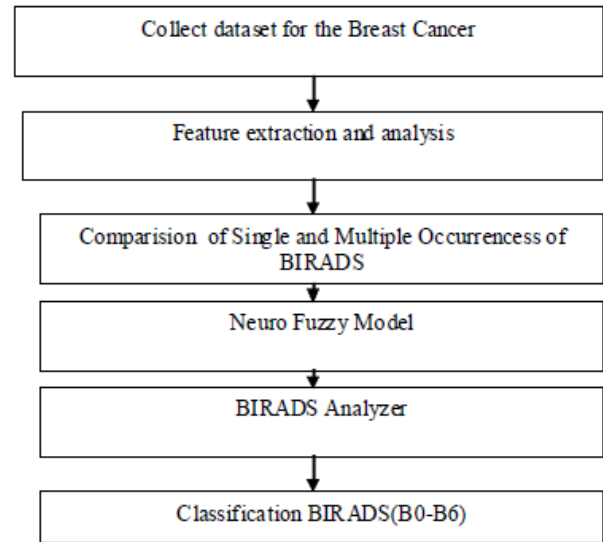
Any pattern classification problem including the hard problems can be represented using a multilayer perceptron

3.2The proposed algorithm

The main difficulty with a multilayer perceptron network is that it is not straightforward to adjust the weights leading in the intermediate layer since the desired output values of the units in these layers are not known. The perceptron learning uses the knowledge of the error and actual output adjust the weights. For the given data only the desired output values of the units in the final output are known. Thus although

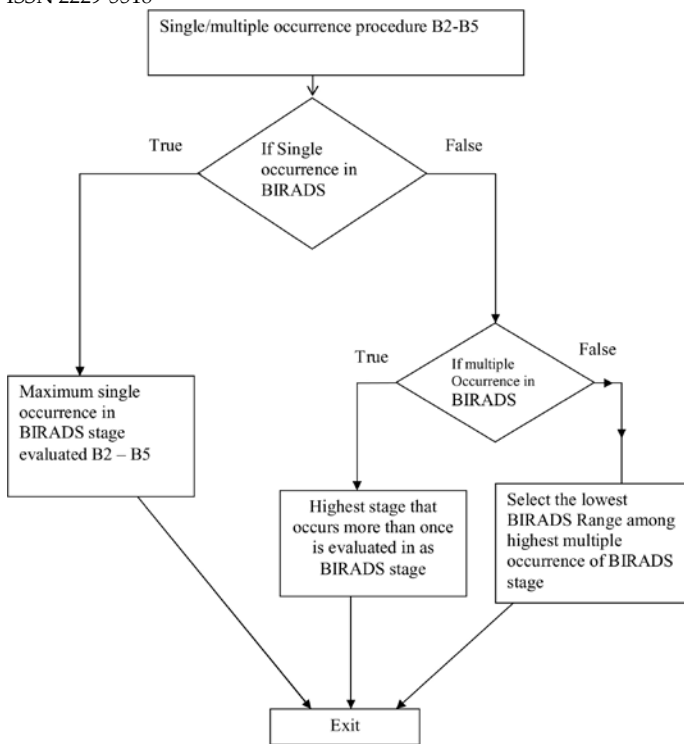
a multilayer perceptron network can handle hard problems the problem of learning or training such a network called hard learning problem.

Novel Diagnostic medical tool for Breast cancer



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The Mammogram dataset contains Asymmetric density, Mass shape, Mass Margin, Mass density, Calcification, Calcification distribution.

1. If Asymmetric density is FALSE and Mass Shape, Mass Margin, Mass density, Calcification and Calcification distribution are nil then BIRADS stage is BO **"Lesions cannot be characterized and need further imaging in the form of MRI, No mass"**
2. If Asymmetric density is TRUE and Mass Shape, Mass Margin, Mass density, Calcification and Calcification distribution are nil then BIRADS stage is B1 ie **"No lesion No abnormality: Normal"**
3. When no multiple occurrences (single occurrence) are found in BIRADS stages B2-B5 the stage that has maximum single occurrence is evaluated as BIRADS stage.
4. When multiple occurrences are present the highest stage that occurs more than once is evaluated as BIRADS stage.
5. If both conditions 3 and 4 does not meet the BIRADS stages then selecting the lowest BIRADS range among highest multiple BIRADS category.
6. If Mass shape is 'irregular', Mass Margin is 'Speculated', Mass Density is "Has Central Lucency", 'Calcification is 'Fine Linear branching /casting' and Calcification Distribution then the BIRADS stage is B6.

4. Conclusion.: The Computer aided medical tool is an accurate tool to overcome the limitation of the current diagnostic system. This algorithm focus on combined selection of single multiple and both occurrences of BIRADS diagnose the stages of the breast cancer. The radiologist has provision to detect the early stages of breast cancer and which leads to evade biopsy.

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