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Texture Classification Using Fuzzy Cognitive Maps for Grading Breast Tumor

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Abstract: Medical decision support system is a complex medical image analysis system that requires an efficient pattern classification tool that is easier to represent and to perform better classification of abnormalities present in medical images. Fuzzy Cognitive Map (FCM) is a simple, efficient cognitive tool used recently to model such complex and dynamic systems. FCM is integrated with medical decision support system that requires grading of suspicious tissues present in human body. FCM is used in this work to grade suspicious breast cancer cells with the texture properties extracted from digital mammograms. The map is constructed using the texture properties as its concepts and are interconnected based on the causal relationship among the concepts. The patterns or the features extracted from the digital mammogram are based on statistical measures suitable to distinguish between normal and abnormal tissues. GLCM (Gray Level Co-occurrence Matrix) and Laws energy measures are statistical methods used in this work to obtain the textural features. The texture concepts used as input for the FCM tool have shown to classify the severity of abnormality present in digital mammograms better than the other classifiers that used training algorithms like neural network, decision trees etc. The outcome of the automated reasoning of FCM is similar to the qualitative assessment tool used by the medical experts.

Key words: Mammogram, GLCM, laws texture, FCM, extracted

INTRODUCTION

A Computer Aided Detection or Diagnosis (CAD) system is an automated medical image analysis system used as an assist for medical experts. The CAD system performs image acquisition, image preprocessing, segmentation and classification. The classification subsystem has a pattern recognition tool to extract features from the image, analyze and classify the patterns or features into classes with a classifier. Textural analyses are done to perform enhanced classification of an image based on their texture properties. Texture is the intensity variation or distribution of pixel intensities that are uniform or non uniform in an image. The mathematical parameters or the texture features derived from the distribution of pixels can determine the texture type that can characterize the nature of the underlying object in a digital image (Castellano *et al*., 2004). Medical image analysis includes study of textural features as an important characteristic of an image for detection or prognosis of a disease. The textural features extracted are characterized from transform methods, structural and statistical methods. The statistical features from an image are calculated by observing the distribution of intensities at a particular location and finding the occurrence of the same distribution in other pixel locations. The statistics of pixel positions with the same combination of intensities are classified into first-order, second-order and higher order. The texture features extracted from first order and second order statistics help radiologists to detect or classify and grade tumors. The work is intended to extract the second order statistical texture features from digital mammograms and grade them as normal, benign and malignant cells. Digital mammograms are radiographs obtained from the screening procedure of the human breast. The screening procedure is recommended mostly for women and rare in men and to women who do not show any signs of tumor in the breast and women aged 40 and above with hereditary factors, familial characteristics, etc. Apart from the screening procedure, a diagnostic procedure requires surgical or radiation treatment. The applicable procedure or treatment to be opted could be decided based on the early detection accuracy of the symptoms through mammogram imaging analysis. The improvement in detection accuracy of the suspicious cells will be helpful to reduce the stress factors in women who are recommended for the screening procedure. A simplified tool for representing the features from the digital mammograms and to grade the suspicious cell is necessary that will augment the subjective opinion

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of radiologists. Fuzzy Cognitive Map is simpler soft computing tool suggested by researchers for the above said requirements.

Literature review: Researchers have proved the development of FCM as intelligent systems for decision analysis in various applications. FCM's are used in medical diagnosis systems that require inductive reasoning to predict the system output. FCM has proven to be an automatic bladder tumor grading model in (Papageorgiou *et al*., 2006) with the help of histopathology clinical report and histopathologists to determine the interconnections among the concepts. The simple structure of the FCM model with easy representation of causal nodes has been exploited to develop an expert system to predict pulmonary infectious disease and also to handle adverse events of the disease in Intensive Care Unit (Papageorgiou *et al*., 2009). A two level architecture FCM is used as a medical support system in obstetrics to improve the maternal complications and fetal distress (Stylios and Georgopoulos, 2010). The FCM has proved to be a worthy soft computing tool in automated systems to forecast artificial emotions (Salmeron, 2012) where there is high degree of uncertainty. Intraductal breast lesions are classified into three categories and the diagnosis infers usual ductal hyperplasia does not require any surgery. FCM is used to classify the intraductal lesions with 93.5% accuracy (Amirkhani *et al*., 2012). Medical support system requires a tool like FCM to assist any critical cases that involves huge amount of data from laboratory tests, imaging reports, clinical examinations etc and data that are missing or vague. The tool with learning algorithms has shown an enhancement in its efficiency and the performance has also been accepted by medical experts (Lucchiari *et al*., 2014). In FCM along with the bagging and boosting procedures have been proposed for autistic disorder prediction helpful for pediatricians and psychiatrists (Papageorgiou *et al*., 2012). The concepts for the FCM were extracted from the architectural and cytologic characteristics (Amirkhani *et al*., 2014) and obtained best response using the FCM model with 94% accuracy. The researchers have incorporated FCM tool for detecting or grading tumors in various medical field and the aim of this work is to grade breast cancer tissue from digital mammograms into the three categories: normal, benign and malignant. The grading of the breast cancer is supported with the BI-RADS assessment tool.

Problem definition: Women who are suspected to have breast abnormalities are recommended to undergo screening or diagnostic procedure depending on the severity of the abnormality. Diagnostic procedure for the suspected individuals is a surgical treatment suggested by medical practitioners based on the inference of the screening process. The digital radiographs-Digital Mammograms from the screening procedure are analyzed by radiologists and augment their findings with a qualitative assessment tool. The classification of the abnormality is expected to have better accuracy that is analogous to the assessment tool the experts believe in order to overcome the diagnostic procedure which is a stress and painful treatment. The complexity of the medical decision support system is that a patient case and symptoms are unique and vary dynamically. A classifier chosen for classification of the abnormality is expected to predict true outcome for any patient with different case history.

Objective of the research work: A soft computing tool for automatic reasoning is required for classifying the abnormalities present in medical images. Fuzzy cognitive map is a simple efficient cognitive tool that is suitable to grade breast tumor. The map facilitates easy representation of the irregularities in medical images as causal nodes and the influence of each node with the others through relationships. The FCM tool uses a learning algorithm that is capable to adjust the impact or influence of the nodes to grade tumor with the help of weights assigned to each causal relationship. FCM is an adjunct to the qualitative assessment tool and will serve as a second opinion to radiologists to grade the tumor. The patients can be prevented to undergo a painful diagnostic procedure based on the outcome of the FCM classifier.

Fuzzy cognitive map representation: Fuzzy Cognitive Map (FCM) is a fuzzy graphical structure enhanced by Kosko (1986) used for modeling causal or inductive reasoning and complex systems. The model is very simple and comprehensible to all type of users. The map is a signed directed, cycle free graph with concepts as causal nodes and the edges representing the relationships among the concepts. The concepts exemplify the features of the system and the interaction among them shows the dynamics of the system. The signed edges represent positive and negative correlation between the concepts. Considering causal relationship between two concepts A and B, a positive correlation is that if A increases then B increases and decrease in A decreases B. The negative correlation is an inverse relationship denoting if A increases then the value of B decreases and decrease in A causes increase in B (Kosko, 1986). Figure 1 is a simple FCM consisting of seven causal nodes.

The edges or the interconnections of the causal nodes are represented by a weight w_{ij} in the range -1 to +1

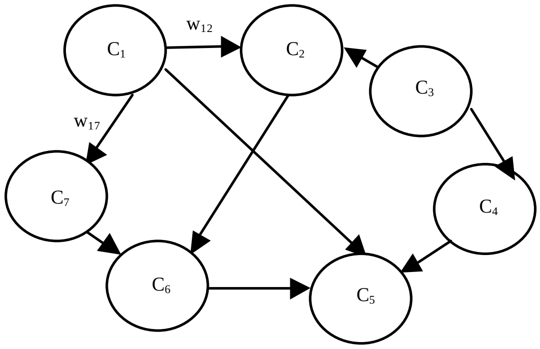

Fig. 1: Fuzzy cognitive Map

that describes the correlation among the concepts. A positive causality between the concepts i and j indicate $w_{ij}>0$ and negative causality between the concepts i and j indicate $w_{ij}<0$ and $w_{ij} = 0$ when there is no relationship between them. The first condition $w_{ij}>0$ denotes an increase in the value of concept i increases the value of concept j. The second condition $w_{ij}<0$ denotes an increase in the value of concept i decreases the value of concept j. The value of each concept A_i is assigned a real value the system determines initially and is within the range 0-1. In the iterative procedure at each step the value of the concept changes based on its previous value and is given by the mathematical notation as in Eq. 1:

$$A^t = f\left(A^{t-1}W + A^{t-1}\right) \quad (1)$$

The FCM is trained with learning algorithms that are similar to neural networks because the concepts and weights are determined by the experts. The subjective opinion of the experts is not consistent and may lead to distortion of the system (Groumpos, 2010). The FCM is refined by adjusting the weights of the concept interconnections with Differential Hebbian learning algorithm.

Hebbian learning rule: Stach *et al*. (2008) had introduced a Data Driven Non Linear Hebbian Learning (DD-NHL) a variant of non linear Hebbian Learning (NHL) that does not depend only on the expert's knowledge and emphasizes that model can be initially built using historical data. A weight matrix is formed based on the number of concepts 'm' chosen by the medical literature. An m×m matrix is initially formed and the intersection of each row and column w_{ij} is the weight assigned between the concepts C_i and C_j. In the weight matrix a concept cannot cause itself and hence the weight w_{ij} where i = j is equal to zero. The weight is updated with value of the concept multiplied by its corresponding weight from the weight matrix as given in the Eq. 2:

$$W_{ij} = -W_{ij} + x_i x_j \quad (2)$$

where, w_{ij} is the weight among the interconnections between the concepts C_i and C_i and $x_i\, x_j$ are the values of the concepts. In a forgetting term, the negative weight value in the right hand side of the Eq. 2 obtained from Oja's rule is used as a stopping criterion to inhibit the growth of the weight value.

Fuzzy cognitive map construction to model breast tumor grading: GLCM (Gray Level Co-occurence Matrix) is the second order statistics and the statistical parameters are the texture features used as one group of concepts for the FCM model. GLCM describes the combination of distribution of the intensities of the pixels in an image. It considers the proximity or reference of a pixel with its neighbor. The descriptions of the GLCM features as described (Pratiwi *et al*., 2015) are given in Table 1. The features listed in the table are considered as concepts for FCM. P(i,j) is an element at position (i,j) in the normalized GLCM, μ is the mean of GLCM, g and n is the number of gray levels in an image and σ is the variance.

Laws energy measures have superior capability to extract quality texture features from the digital mammograms (Setiawan *et al*., 2015). Laws texture measures extracts the level, edge, spot and ripple characteristics from an image. The equations of the Laws texture are given in Eq. 3. Each 5×1 vector named as L5 (level), E5 (edge), S5 (spot), R5 (ripple) of Laws measure is multiplied with the other vector to form 15, 5×5 filter masks. Each filter is applied to the image and the energy is computed by taking the average of the neighborhood of the pixel under consideration. The energy measures are L5E5, E5L5, L5R5, R5L5, E5S5, S5E5, S5S5, R5R5, L5S5, S5L5, E5E5, E5R5, R5E5, S5R5 and R5S5. Among the 15 masks the average of few masks are taken. The average energy of L5E5 and E5L5 is calculated and likewise the averages of all other similar measures are calculated. A total of 9 energy measures from Laws texture are considered as concepts C15- C23 for the FCM. The concept values are normalized and they are between the ranges 0-1.

L5= [1, 4, 6, 4, 1] (Level)
E5= [-1,-2, 0, 2, 1] (Edge)
S5= [-1, 0, 2, 0, 1] (Spot)
R5= [1,-4, 6,-4, 1] (Ripple) (3)

From the equations of GCLM and with a survey of literature (Setiawan *et al*., 2015; Ananda and Thomas, 2010) the correlation between the concepts could be inferred. There is a positive or a negative correlation between the features extracted from GLCM and the relationship is listed in Table 2.

Table 1: List of GLCM features

Concept-Id	GLCM feature	Description	Formulae
C1	Auto correlation	The measure describes the correlation of a combination pair with the other combination pairs	$AC = \sum_{i=1}^{n}\sum_{j=1}^{n}(ij)P(i,j)$
C2	Energy	It measures the uniformity of image that is pixel pair repetitions and detects disorders in textures. It is also called as Angular Second Moment	$E = \sum_{i=1}^{n}\sum_{j=1}^{n}P(i,j)^2$
C3	Contrast	It measures the amount of local variations present in the image	$C = \sum_{i=1}^{n}\sum_{j=1}^{n}\lvert i-j\rvert^2 \times P(i,j)$
C4	Entropy	This statistic measures the disorder or complexity of an image. The entropy is large when the image is not texturally uniform	$H = \sum_{i=1}^{n}\sum_{j=1}^{n}\frac{P(i,j)}{1+\lvert i-j\rvert}$
C5	Homogeneity	This statistic is also called as Inverse Difference Moment. It measures the relative smoothnesss of the intensity in the region	$e = -\sum_{i}\sum_{j}P(i,j)\log_2 P(i,j)$
C6	Dissimilarity	It measures the difference in the gray level pairs in an image	$D = \sum_{ij}\lvert i-j\rvert p(i,j)$
C7	Correlation	It measures of gray tone linear dependencies in the image	$Cor = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\{i\times j\}\times P(i,j)\{\mu x\times \mu y\}}{\sigma x\times \sigma y}$
C8	Sum Entropy	The measure describes the size of irregular shape of the image under consideration	$SE = \sum_{1=2}^{2Ng}p_{x+y}\{p_{x+y}(i)\}$
C9	Sum Variance	This measure the weights of elements that differ from the average value of the GLCM	$SV = \sum_{i=2}^{2Ng}(i-SE)^2 p_{x+y}$
C10	Cluster Tendency	This measure indicates the number of clusters that can classified from the gray level of the image	Cluster tendency = $\sum_{i}\sum_{i}(i+j-2\mu)P(i,j)$
C11	Cluster Shade	The measure defines lack of symmetry	Cluster shade = $\sum_{i=0}^{g-1}\sum_{j=0}^{g-1}\{i+j-\mu_x-\mu_y\}^3\times P(i,j)$
C12	Maximum probability	Strongest response of the co-occurence matrix	$MP = Max_{(i,j)}P_{(i,j)}$
C13	Sum of squares variance	This statistic discriminates that pixel that highly differs from the average value of pixel at (i,j)	$V = \sum_{i=1}^{n}\sum_{j=1}^{n}(i-\mu)^2 P(i,j)$
C14	Cluster prominence	The low measure indicates less variation in gray scales	$ClusterP = \sum_{i=0}^{g-1}\sum_{j=0}^{g-1}\{i+j-\mu_x-\mu_y\}^4\times P(i,j)$

Table 2: Relationship among the GCLM features

GCLM Feature andoncept Id	GCLM Feature andoncept Id	Relationship
Homogeneity (C5)	Dissimilarity (C6)	Negative
Contrast (C3)	Dissimilarity (C6)	Positive
Entropy (C4)	Dissimilarity (C6)	Positive
Entropy (C4)	Homogeneity (C5)	Negative
Entropy (C4)	Angular Second Moment (Energy) (C2)	Negative
Homogeneity (C5)	Contrast (C3)	Negative

FCM is constructed combining 14 features from GLCM and 9 from Laws texture features and a decision concept to determine the grading of the tumor summing up to 24 concepts as given in Fig. 2. The interrelationship among the concepts is formed from the literature and the initial weights w_{ij} between the concepts are computed

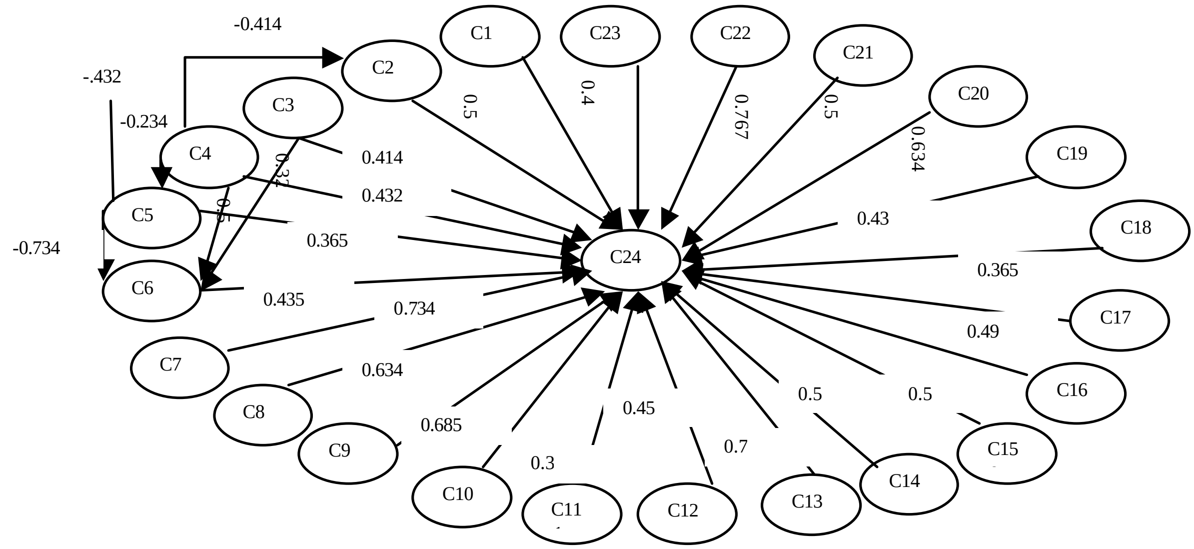

Fig. 2: Fuzzy cognitive map to grade breast cancer

using genetic algorithm The initial weights are assigned to all the concepts using genetic algorithm so that a compatible membership value is assigned equivalent to expert's decisions. The weights are altered and reassigned after few iterations of the learning algorithm. The weights have been fixed for each edge as illustrated in Fig. 2. The C24 is the decision concept to grade the breast tumor based on the 23 causal nodes extracted from GLCM and Laws measures.

MATERIALS AND METHODS

Mini-MIAS database (Suckling *et al*., 1994) is the benchmark Digital Mammogram database used for study that has been categorized based on the background tissue characteristics like fatty, fatty-glandular and dense-glandular and classes based on the abnormalities like calcification, circumscribed mass, asymmetry, well-defined mass, spiculated mass, architectural distortion and normal. The database describes the classes based on the severity of the abnormalities as classified from the well known BI-RADS quality assurance tool. Image processing toolbox of Matlab 2013a was adopted. The 48 images from the MIAS database was retrieved and preprocessed using the well known image preprocessing CALHE algorithm. The tool box provided options to retrieve texture features from GLCM.

RESULTS AND DISCUSSION

Among the images from the MIAS database only mammograms with dense glandular in nature was chosen for study. The database has 48 images that are dense glandular in nature classified from BI-RADS tool that are normal, benign and malignant. From the set of 48 images, 8 normal images, 13 benign and 27 malignant images were chosen to be input for the FCM tool. Since FCM tool uses a supervised learning algorithm and with the aid of BI-RADS classification, the decision concept C24 was assigned value 1 for the set of features with malignant abnormality, 0.5 for benign and 0 for normal digital mammograms. The blue marks refer to normal class, the green marks refer to benign and the red as malignant indicated in Fig. 3. Class A refers to normal class, Class B refers to benign and Class C is malignant class as denoted in Table 3.

It is clearly indicated from Fig. 3 and Table 3 that the FCM tool has shown 100% accuracy in classifying the normal class, 85% classification accuracy of benign class and 93% accuracy in classifying malignant class.

The same set of texture features (GLCM and the Laws) was used as input for the other well known classifiers like Naïve Bayes, Multilayer Perceptron, Decision trees and Support Vector Machine. The open source WEKA tool was used to compare the FCM classification performance with the other classification algorithms. The sensitivity and specificity (Zhu *et al*., 2010) is described in Eq. 4 and 5:

$$\text{Sensitivity} = TP/(TP + FN) \tag{4}$$

$$\text{Specificity} = TN/(TN + FP) \tag{5}$$

Where:
TP = True Positive
FN = False Negative
TN = True Negative
FP = False Positive

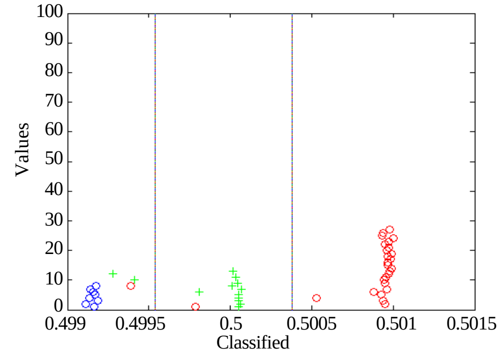

Fig. 3: The classified classes based on the severity of abnormaly

Table 3: Classification of normality, benign and abnormality classes from digital mammogram imaging

	Class			Class			Class			Class			Class		
Factors	A	B	C	A	B	C	A	B	C	A	B	C	A	B	C
Sensitivity = TP/(TP+FN)	1.0	0.53	0.77	0.62	0.53	0.92	0.75	0.61	0.88	1.0	0.84	0.92	0.62	0.30	0.74
Specificity = TN/(FP+TN)	0.92	0.85	0.80	0.97	0.85	0.76	0.95	0.88	0.80	0.92	0.97	1.0	0.90	0.77	0.66

Table 4: The comparative measures of different learning algorithms

Classifiers/ confusion	Naive Bayes			MLP - ANN			SMO			FCM			Decision trees		
matrix	A	B	C	A	B	C	A	B	C	A	B	C	A	B	C
Class A	8	0	0	5	3	0	6	2	0	8	0	0	5	3	0
Class B	2	7	4	1	7	5	1	8	4	2	11	0	2	4	7
Class C	1	5	21	0	2	25	1	2	24	1	1	25	2	5	20
Per class accuracy (%)	100	54	78	63	54	93	75	62	89	100	85	93	63	31	74
Overall accuracy (%)	75			77.0833			79.1667			91.666			60.4167		

Sensitivity is the true positive assessment and specificity is true negative assessment of the disease. In other words, the number of cases that are actually identified as true or positively recognized to have the disease is sensitivity and specificity is the number of cases that are actually identified or truly recognized as not having the disease. From Table 4, it can be inferred that FCM has identified better than the other classifiers, the mammograms based on their severity of abnormality.

CONCLUSION

FCM can be used as an automated tool to augment the well known BI-RADS tool for grading tumor. It is a simple cognitive tool that can be easily used by medical practitioners for classifying the abnormalities present in mammograms. The irregularities in the image can be easily represented as causal nodes of FCM and the influence of the causal nodes on the others can be adjusted through the relationships. The sensitivity of Class A (normal), Class B(benign), Class C (malignant) is 1.0, 0.84 and 0.92. The specificity of Class A-C is 0.92, 0.97 and 1.0. The sensitivity and specificity values have shown that FCM tool has shown better classification accuracy than the other well known classifiers.

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