Diagnosis of Breast Masses from Dynamic Contrast-Enhanced and Diffusion-Weighted MR: A Machine Learning Approach

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Abstract

Purpose: Dynamic contrast-enhanced magnetic resonance imaging (DCE-MRI) is increasingly used for breast cancer diagnosis as supplementary to conventional imaging techniques. Combining of diffusion-weighted imaging (DWI) of morphology and kinetic features from DCE-MRI to improve the discrimination power of malignant from benign breast masses is rarely reported.

Materials and Methods: The study comprised of 234 female patients with 85 benign and 149 malignant lesions. Four distinct groups of features, coupling with pathological tests, were estimated to comprehensively characterize the pictorial properties of each lesion, which was obtained by a semi-automated segmentation method. Classical machine learning scheme including feature subset selection and various classification schemes were employed to build prognostic model, which served as a foundation for evaluating the combined effects of the multi-sided features for predicting of the types of lesions. Various measurements including cross validation and receiver operating characteristics were used to quantify the diagnostic performances of each feature as well as their combination.

Results: Seven features were all found to be statistically different between the malignant and the benign groups and their combination has achieved the highest classification accuracy. The seven features include one pathological variable of age, one morphological variable of slope, three texture features of entropy, inverse difference and information correlation, one kinetic feature of SER and one DWI feature of apparent diffusion coefficient (ADC). Together with the selected diagnostic features, various classical classification schemes were used to test their discrimination power through cross validation scheme. The averaged measurements of sensitivity, specificity, AUC and accuracy are 0.85, 0.89, 90.9% and 0.93, respectively.

Conclusion: Multi-sided variables which characterize the morphological, kinetic, pathological properties and DWI measurement of ADC can dramatically improve the discriminatory power of breast lesions.

Introduction

The development of noninvasive methods of tissue characterization that could be applied early in the course of diagnosis to assess risk and to guide subsequent treatment would allow clinicians to tailor therapy on an individual. Conventional magnetic resonance imaging (MRI) of the breast has proven to be less successful than expected [1]. Breast MRI has demonstrated a high sensitivity, but with the shortcoming of varying specificity, reported to be from 37% to 97% [2,3,4], and therefore multiple biopsies tests have to be conducted as supplementary. Recently, more specialized methods, including dynamic contrast-enhanced magnetic resonance imaging (DCE-MRI) and diffusion-weighted magnetic resonance imaging (DW-MRI), have advanced to the point where they provide quantitative measurements of tissue properties that are highly related to the assessing of tumor progression and/or responses [1,2,5,6,7]. DW MRI was designed to reflect water movement within tissues by measuring the degree of random molecular motion and quantify such movement with apparent diffusion coefficient (ADC) value. Recent studies [8,9,10,11,12,13] found that the ADC is significantly lower in malignant tumors than in benign breast lesions or normal tissue in
DW MRI. This special observation is mainly due to a high cell density, caused by an increased restriction of the extracellular matrix and an increased fraction of the signal from intracellular water [8,11,14].

The advances in imaging techniques allow for the possibility to investigate the diagnostic performance by combining the merits of different image modalities. Such investigation is promising in clinical diagnosis by reducing inter-observer biases in interpretation of the images [15,16], and by shortening the diagnosis time [17]. For example, it has been shown that the morphological features in breast MRI as adjunct diagnostic criteria can improve the specificity without significantly reducing the sensitivity [18,19,20]. Combining morphological characteristics with enhancement kinetics can also improve the diagnostic performance of breast lesion interpretation [21]. Yabuuchi et al. [22] reported a high accuracy in enhancing breast masses through the combination of DWI and DCE-MRI features.

However, there are few researches on investigation of the combinational performance of both MRI and DWI in discriminating of pathologically verified breast masses. In the current study, we retrospectively investigated the potential discriminatory power of image features estimated from both of DWI and DCE-MRI. Four distinct groups of features were estimated to comprehensively characterize the image in a multi-sided way. To remove the redundancy as well as to increase the diagnosis capabilities of the features, a hybrid feature selection scheme was conducted on the four feature groups and a pathological variable. The resulted seven features, including one for pathology, were widely tested by standard classification models to demonstrate their combinational prognostic capabilities.

| Table 1. | Histopathology of benign and malignant breast lesions. |
|----------------------------------|----------------|
| Tumor group               | Number | Percentage |
| Malignant lesions        | 149    | 63.68       |
| Invasive ductal carcinoma | 120    | 51.3        |
| Intraductal carcinoma    | 17     | 7.26        |
| Ductal carcinoma in situ | 4      | 1.7         |
| Mucinous carcinoma       | 3      | 1.28        |
| Medullary carcinoma      | 1      | 0.43        |
| Others                   | 4      | 1.71        |
| Benign lesions           | 85     | 36.32       |
| Fibroadenoma             | 26     | 11.11       |
| Fibrocystic changes      | 24     | 10.26       |
| Fibroadenosis            | 3      | 1.28        |
| Intraductal papilloma    | 4      | 1.7         |
| Hyperplasia              | 3      | 1.28        |
| Phyllodes tumor          | 2      | 0.85        |
| Adenomysis epithelioma   | 1      | 0.43        |
| Inflammation             | 1      | 0.43        |
| Follow-up                | 21     | 8.97        |

1) **Kinetic features:** The shape of time-signal intensity curve has been shown to be an important criteria in differentiating benign from malignant breast lesions [23]. Both of the early-phase enhancement and the signal enhancement ratio (SER) [24] were estimated to represent the kinetic behavior of the lesion signal intensity of lesion before and after the injection of Gd-DTPA. They are defined as:

\[
\text{Early-phase Enhancement} = \frac{I_1 - I_0}{I_0} \times 100 \quad [25],
\]

\[
\text{SER} = \frac{I_1 - I_0}{I_{last} - I_0}
\]

where \(I_0, I_1, \) and \(I_{last} \) represent the signal intensity in the pre-contrast, the first post-contrast and the last images, respectively. The morphology and enhancement kinetic features were also investigated to determine their diagnostic performance to differentiate between malignant and benign lesions that present as mass versus non-mass types [26,27].
Morphological Features: The manually identified lesion was further segmented to have its contours. The segmentation used a two-step approach to incorporate fuzzy c-means (FCM) clustering [28] and gradient vector flow (GVF) snake algorithm [29]. Once the lesion was segmented, eleven morphological features were calculated to quantify its morphological characteristics. The lexicon by using morphology characteristics, such as shape and margin categories, have long been adopted in discrimination of breast lesion [30]. Its diagnostic capability were also widely studied by combining it with various factors, such as kinetic descriptor [31], texture features [26,32] and DWI [33]. In the current study, eleven morphological features include compactness, spiculation, extent, elongation, solidity, circularity, entropy of radial length distribution, fractal, heterogeneity, area, and eccentricity were borrowed to serve as morphological characterization. Inclusion of the eleven features followed a strict criteria: either they are used in clinical practice or have been reported to be effective [30,34]. An illustrate examples is shown in Figure 1.

Texture Features: The textural attributes evaluated via GLCM method were combined with morphologic descriptors in DCE-MRI to achieve a nice discrimination power [30,31,32,35]. It has also been reported that MRI texture features are significantly associated with breast tumor subtype and neoadjuvant therapy response. Thirteen texture features were estimated on the segmented lesion through its gray level co-occurrence matrix (GLCM) [36]. The texture features included: angular second moment, contrast, correlation, inverse difference moment, sum average, sum variance, sum entropy, entropy, difference average, difference variance, difference entropy, information measure of correlation 1, and

Figure 1. Segmentation of a sample breast lesion on MRI, confirmed as Invasive ductal carcinoma, for a 50 year old woman. (a) Area including a suspicious breast lesion is highlighted by a blue rectangle; (b) Initial segmentation result on (a) by using FCM-based method; (c) Final segmented lesion after GVF snake model initialized from (b).

Figure 2. A sample image of fibroadenoma for a 28 year woman. (a) Raw dynamic contrast-enhanced MR image on lesion, which exhibits high signal intensity. The mass-like enhancement area is marked by purple arrow and the lesion; (b) Raw Diffusion-weighted MR image (b = 800 s/mm²); (c) Calculated ADC map from (b). Lesion area exhibits with light green (pointed in purple arrow), implying a high ADC value. ADC measured in this lesion is $1.91 \times 10^{-2}$ s/mm².

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information measure of correlation 2 [36]. This feature group is widely used in field of pattern recognition, such as handwriting discrimination [37,38], and medical image analysis [39,40]. Readers can refer to File S1 for the rigorous mathematical definitions of the pictorial features.

3) DWI Features: The apparent diffusion coefficient (ADC) value was used to quantify the Diffusion weighted (DW) MRI. Firstly, the region of interests (ROIs) were manually drawn on the diffusion-weighted images (b = 800 s/mm²) (Figure 2) by carefully inspecting the regions with high signal. ROIs that were larger than 20 mm² were considered meaningful and therefore retained for further analysis [41]. Then the DWI intensity for each lesion was dichotomized into low and high values by that of the corresponding background breast tissue. Finally, the mean ADC values were then obtained to serves as the quantification of the DWI characteristics.

The status of breast masses enrolled in the study was all verified in histopathology, or confirmed by at least two years of follow-up subsequently. Therefore, the features aforementioned, coupling with the lesion status, can be considered as a binary classification problem.

Diagnostic Feature Selection

Univariate analysis is limited since it ignores the role of combinational potentials which could provide a good classification. Therefore, we conducted firstly on the selection of a subgroup of informative variables that were able to distinguish malignant lesions from benign ones. This process is known as feature subset selection (FSS) [42,43,44,45].

Feature selection algorithms usually fall into two categories [42]: filter and wrapper methods. Filter selects subsets of features as a preprocessing step, independently of the chosen predictor. In comparison, wrapper uses a base classifier to score subsets of features according to their predictive power. In many cases, wrapping with classical classifiers such as Support Vector Machine [44], Naive Bayes [46] and Nearest Neighbors produce comparable performance [47]. The wrapper has the advantage of better performance; however, its usage in biomedical area is limited due to its high computational cost [42]. To alleviate this problem, we used a hybrid filter-wrapper algorithm [48]. In this hybrid feature

![Diagram](Figure 3. The workflow of the hybrid FSS scheme to have a compact but informative feature subset. doi:10.1371/journal.pone.0087387.g003)

| Table 2. The features removed after Step 2–4 by using the proposed FSS algorithm. |
|---------------------------------|-------------------------------------------------|
| Step 2: Heterogeneity, Rectangular degree, Elongation, Eccentricity |
| Step 3: Fractal dimension, Circularity, Spiculation, Area, Correlation, Inertia, Sum Variance, Sum entropy, Difference Average, Difference Average, Difference Entropy. |
| Step 4: Compactness, Solidity, Entropy of Radial Length Distribution, Energy, Sum Average, Information Correlation 2 |
| Final Output: ADC, Slope, SER, Age, Entropy, Inverse Difference, Information Correlation 1 |

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selection model, the features were firstly filtered by t-test to find out the statistically significant variables with confidence level of 95%. The 24 variables obtained are then gone through FSS via the wrapper of the classifier of SVM. To alleviate computation cost in wrapping, genetic algorithms was used to find out an informative subset was obtained. The main advantage of this hybrid approach is that it remains a great part of advantages in wrapper, while the features removed after each step and the resulted compact subset was obtained. The final step, each feature left was examined through the classification test by SVM to remove the features whose contribution to classification accuracy is negligible when it was omitted. Therefore, a compact but highly informative feature subset was obtained. The main advantage of this hybrid approach is that it remains a great part of advantages in wrapper, while reducing the computation cost greatly. We draw a workflow to illustrate the hybrid FSS algorithm in Fig. 3. Table 2 summarized the features removed after each step and the resulted compact features.

Classification Model

The combination of the parameters as a whole could reflect different aspects of lesion properties and is potentially a comprehensive approach to characterize lesion status [49]. The differentiation of malignant from benign lesions was treated as a two-class pattern classification problem. Classical classification algorithms, including support vector machine (SVM) [44], Naive Bayes (NB), k-nearest neighbors (KNN), and logistic regression (LR) model, were used to evaluate the diagnostic performance of the carefully selected variables [44,47,50]. To make an extensive comparison, the derived classier was evaluated through ten-fold cross validation scheme. In the scheme, the data were randomly divided into ten equal sized subsets, among which 9 subsets were trained to find out the classifier or optimal cut-off values and the one left behind was used for testing. For the group in which only one feature was selected, univariate analysis was carried out by Receiver Operating Characteristics (ROC). For the feature group which has more than two features, classical classification algorithms including SVM, Naive Bayes (NB), KNN and Logistic Regression were conducted and their averaged performance was calculated.

The experimental results were summarized in Table.4. When only individual feature group was used, the prediction performance was unsatisfactory. For example, the accuracy is 63.4% by using morphology features. While the accuracy increases to 74.9% by using DWI feature of ADC,. The observation implies two aspects: 1) characterization of the lesion through one-sided methodology was not comprehensive enough. It might have good sensitivity, yet the specificity was poor; 2) ADC is a nice diagnostic factor for discriminating the status of breast mass. Our finding is consistent with earlier results [8,11,14]. However, the specificity of ADC was lower than what’s anticipated, making it an unreliable factor in diagnostic practice as a result.

In comparison, when all the well selected features were combined together, the averaged sensitivity, specificity, AUC and accuracy of the classification model dramatically increased to 0.85, 0.89, 0.93 and 90.9%, respectively (Table 4). Among the tested models, although SVM achieved superior performance to other three models in terms of accuracy, the latter ones had comparable results. Therefore, we may draw a conclusion that a full characterization of breast lesion through multi-sided methodologies will produce a high discrimination power.

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**Table 3.** Group mean, P values and diagnostic accuracy of selected parameters.

| Parameters                  | Mean±SD   | p^1 value | Diagnostic^2 Accuracy | Threshold Value |
|-----------------------------|-----------|-----------|-----------------------|-----------------|
|                            | Benign    | Malignant |                       |                 |
| Age                         | 48.38±11.13 | 39.09±8.11 | <0.001                | 68.8%           | 43              |
| Slope                       | 1.82±0.93  | 2.65±0.88  | <0.001                | 76.4%           | 1.98            |
| Entropy                     | 9.98±1.11  | 10.13±1.03 | <0.001                | 74.2%           | 7.90            |
| Inverse Difference          | 0.13±0.03  | 0.14±0.02  | <0.001                | 69.1%           | 0.118           |
| Information Correlation 1   | -0.50±0.12 | 0.40±0.11  | <0.001                | 71.6%           | -0.33           |
| ADC                         | 1.69±0.34  | 1.17±0.24  | <0.001                | 86.6%           | 1.85            |
| SER^3                       | 0.69±0.34  | 1.28±0.34  | <0.001                | 87.6%           | 0.34            |

^1Computed with paired-sample t-test.  
^2Computed with Receiving Operating Characteristic.  
^3Signal enhancement ratio.  

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Diagnostic Performance of the Combined Features

In this experiment, we evaluated the diagnostic performance of each individual feature group as well as their combinations through ten-fold cross validation scheme. The whole data were randomly divided into ten equal sized subsets, among which 9 subsets were trained to find out the classifier or optimal cut-off values and the one left behind was used for testing. For the group in which only one feature was selected, univariate analysis was carried out by Receiver Operating Characteristics (ROC). For the feature group which has more than two features, classical classification algorithms including SVM, Naive Bayes (NB), KNN and Logistic Regression were conducted and their averaged performance was calculated.

The results of diagnostic performance of each Feature Individually

The proposed feature selection algorithm produced seven features, including one morphology (slope) and three texture (entropy, inverse difference, information correlation 1) parameters, one kinetic parameter (SER), one pathological parameter (age) and ADC. Univariate statistical analyses were conducted to demonstrate the diagnostic capabilities of each feature. All features selected were shown to be statistically different between malignant and benign lesions. Table 3 summarizes the mean and standard deviation and the diagnostic performance on the whole dataset of the seven selected parameters. Among the seven parameters, the diagnostic accuracy of SER was the highest.

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Breast Masses Diagnosed by Machine Learning Method
The results of our study demonstrate that diagnostic performance can be dramatically improved by incorporating the multi-sided characterizations of the breast lesions on MRI. In particular to the parameter of ADC, it has been shown to be correlated to lesion malignancy due to a high cell density, caused by an increased fraction of signals coming from intracellular water. This parameter, when combined with morphology and enhancement kinetic features, will increase in both specificity and sensitivity in discriminating types of lesions, thus it is promising in providing a supplementary assessment on lesion status.

We carried out a systematical analysis to investigate the potential power in discriminating a fully comprised pictorial characterization of lesions. Our analysis pipeline includes image segmentation, feature extraction, selection and classification model building. The seven features obtained are all shown to be statistically different between the malignant and benign lesions.

Discussion

The combined features were tested extensively through four popular classification models. The finding demonstrates that the combination of the kinetic enhancement data, morphology information and ADC in a systematic model is effective and comprehensive to make an accurate diagnosis on breast masses. We speculate that this could potentially impact clinical management decisions and therapy selection.

Supporting Information

File S1  Quantitative measurements of breast lesions. (DOCX)

Author Contributions

Conceived and designed the experiments: LL. Performed the experiments: YP CO. Analyzed the data: HC. Contributed reagents/materials/analysis tools: MC. Wrote the paper: HC YP.

References

1. Delille JP, Slanetz PJ, Yeh ED, Halpern EF, Kopans DB, et al. (2003) Invasive ductal breast carcinoma response to neoadjuvant chemotherapy: Noninvasive monitoring with functional MR imaging - Pilot study. Radiology 228: 63–69.
2. Schellhout K, Van Goethem M, Kerschot E, Colpaert C, Schellhout AM, et al. (2004) Contrast-enhanced MR imaging of breast lesions and effect on treatment. Eur J Surg Oncol 30: 501–507.
3. Jansen SA, Fan X, Karzmar GS, Abe H, Schmidt RA, et al. (2008) DCEMRI of breast lesions: is kinetic analysis equally effective for both mass and nonmass-like enhancement? Med Phys 35: 3102–3109.
4. Zhang Y, Fukatsu H, Naganawa S, Satake H, Sato Y, et al. (2002) The role of contrast-enhanced MR mammography for determining candidates for breast conservation surgery. Breast Cancer 9: 231–239.
5. Kuhl CK, Schrading S, Leutner CC, Morakabati-Spitz N, Wardelmann E, et al. (2003) Mammography, breast ultrasound, and magnetic resonance imaging for surveillance of women at high familial risk for breast cancer. J Clin Oncol 21: 8469–8476.
6. Tillman GF, Orel SG, Schnall MD, Schulz DJ, Tan JE, et al. (2002) Effect of breast magnetic resonance imaging on the clinical management of women with early-stage breast carcinoma. J Clin Oncol 20: 3413–3423.
7. Sardanelli F, Boetes C, Borisch B, Decker T, Federico M, et al. (2010) Magnetic resonance imaging of the breast: recommendations from the EUSOMA working group. Eur J Cancer 46: 1296–1316.
8. Hatakenaka M, Soeda H, Yabuuchi H, Matsuo Y, Kamitani T, et al. (2008) Apparent diffusion coefficients of breast tumors: clinical application. Magn Reson Med Sci 7: 23–29.

Table 4. Diagnostic performances for differentiating between malignant and benign lesions on various feature sets via 10 fold CV.

| Diagnostic Feature | Evaluation Model | Sensitivity | Specificity | Accuracy | AUC  |
|--------------------|------------------|-------------|-------------|----------|------|
| Morphology Features (Slope) | Univariate Threshold | 0.74 | 0.46 | 63.4% | 0.60 |
| Kinetics Features (SER) | Univariate Threshold | 0.79 | 0.52 | 68.7% | 0.66 |
| DWI Feature (ADC) | Univariate Threshold | 0.95 | 0.52 | 74.9% | 0.69 |
| Texture Features (Entropy, Inverse difference Information correlation 1) | SVM | 0.51 | 0.68 | 72.4% | 0.68 |
| ADC +Morphology +Kinetics +Pathology | SVM | 0.86 | 0.94 | 92.4% | 0.91 |
| ADC +Morphology +Kinetics +Pathology | NB | 0.56 | 0.65 | 72.0% | 0.78 |
| ADC +Morphology +Kinetics +Pathology | KNN(n = 6) | 0.64 | 0.59 | 69.8% | 0.72 |
| ADC +Morphology +Kinetics +Pathology | Logistic Regression | 0.57 | 0.70 | 74.6% | 0.71 |
| ADC +Morphology +Kinetics +Pathology | Averaged | 0.57 | 0.66 | 72.2% | 0.72 |
| ADC +Morphology +Kinetics +Pathology | NB | 0.86 | 0.89 | 90.5% | 0.95 |
| ADC +Morphology +Kinetics +Pathology | KNN(n = 6) | 0.85 | 0.871 | 89.5% | 0.94 |
| ADC +Morphology +Kinetics +Pathology | Logistic Regression | 0.86 | 0.91 | 91.3% | 0.90 |
| ADC +Morphology +Kinetics +Pathology | Averaged | 0.85 | 0.89 | 90.9% | 0.93 |

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17. Wood C (2005) Computer Aided Detection (CAD) for breast MRI. Technol Cancer Res Treat 4: 49–53.
18. Malich A, Fischer DR, Wurdinger S, Boeticher J, Marx C, et al. (2005) Potential MRI interpretation model: differentiation of benign from malignant breast masses. Am J Roentgenol 185: 964–970.
19. Baum F, Fischer U, Vosheinrich R, Grabbe E (2002) Classification of hypervascularized lesions in CE MR imaging of the breast. Eur Radiol 12: 1087–1092.
20. Wedgegarner U, Bick U, Wortler K, Rummenny E, Bongartz G (2003) Differentiation between benign and malignant findings on MR-mammography: usefulness of morphological criteria. Eur Radiol 11: 1645–1650.
21. Kuhl CK (2000) MRI of breast tumors. Eur Radiol 10: 46–56.
22. Yabuchi H, Matsu Y, Okahji T, Kunitani T, Sodek H, et al. (2008) Enhanced mass on contrast-enhanced breast MR imaging: lesion characterization using combination of dynamic contrast-enhanced and diffusion-weighted MR images. J Magn Reson Imaging 28: 1157–1165.
23. Orel SG (1999) Differentiating Benign from Malignant Enhancing Lesions Identified at MR Imaging of the Breast: Are Time-Signal Intensity Curves an Accurate Predictor? Radiology 211: 5–7.
24. Hyborn NM (2001) Vascularity assessment of breast lesions with gadolinium-enhanced MR imaging. Magn Reson Imaging Clin N Am 9: 321–332.
25. Kuhl CK, Mielcarek P, Klaschik S, Leutner C, Wardelmann E, et al. (1999) Dynamic breast MR imaging: are signal intensity time course data useful for differential diagnosis of enhancing lesions? Radiology 211: 101–110.
26. Newell D, Nie K, Chen J, Hsu C, Yu H, et al. (2010) Selection of diagnostic features on breast MRI to differentiate between malignant and benign lesions using computer-aided diagnosis: differences in lesions presenting as mass and non-mass-like enhancement. European Radiology 20: 771–781.
27. Meinel LA, Stolpen AH, Berbaum KS, Fajardo LL, Reinhardt JM (2007) Breast MRI lesion classification: Improved performance of human readers with a backpropagation neural network computer-aided diagnosis (CAD) system. Journal of Magnetic Resonance Imaging 25: 89–95.
28. Wu K (2012) Analysis of parameter selections for fuzzy c-means. Pattern Recognition 45: 407–415.
29. Xu C, Prince JL (1998) Snakes, shapes, and gradient vector flow. IEEE Trans Image Process 7: 359–369.
30. Pang Y, Li L, Hu W, Peng Y, Liu L, et al. (2012) Computerized segmentation and characterization of breast lesions in dynamic contrast-enhanced MR images using fuzzy c-means clustering and snake algorithm. Comput Math Methods Med 2012: 634907.
31. Agner SC, Soman S, Llibeld E, McDonald M, Thomas K, et al. (2011) Textural kinetics: a novel dynamic contrast-enhanced (DCE-MRI) feature for breast lesion classification. Journal of Digital Imaging 24: 446–463.
32. Nie K, Chen J, Yu HJ, Chu Y, Nalcioglu O, et al. (2008) Quantitative Analysis of Lesion Morphology and Texture Features for Diagnostic Prediction in Breast MRI. Academic Radiology 15: 1513–1525.
33. Yankeelov TE, Lepage M, Chakravarthy A, Broune EE, Niermann KJ, et al. (2007) Integration of quantitative DCE-MRI and ADC mapping to monitor treatment response in human breast cancer: initial results. Magn Reson Imaging 25: 1–13.
34. Orel SG, Schnall MD, LiVolsi VA, Truong RH (1994) Suspicious breast lesions: MR imaging with radiologic-pathologic correlation. Radiology 190: 485–493.
35. Gibbs P, Turnbull LW (2005) Textural analysis of contrast-enhanced MR images of the breast. Magnetic Resonance in Medicine 50: 92–98.
36. Chen W, Gieger ML, Li H, Bick U, Newstead GM (2007) Volumetric texture analysis of breast lesions on contrast-enhanced magnetic resonance images. Magnetic Resonance in Medicine 58: 362–371.
37. Xie X (2008) A review of recent advances in surface defect detection using texture analysis techniques. Electronic Letters on Computer Vision and Image Analysis 7: 1–22.
38. Liu G, Yang J (2008) Image retrieval based on the textron co-occurrence matrix. Pattern Recognition 41: 3521–3527.
39. Wu H, Sun T, Wang J, Li X, Wang W, et al. (2013) Combination of radiological and gray level co-occurrence matrix textural features used to distinguish solitary pulmonary nodules by computed tomography. Journal of Digital Imaging 4: 787–802.
40. Lopez R, Ayache A, Makri N, Puech P, Villers A, et al. (2011) Prostate cancer characterization on MR images using fractal features. Medical physics 38: 83–95.
41. Partridge SC, DeMartini WB, Kurland BF, Eby PR, White SW, et al. (2009) Quantitative diffusion-weighted imaging as an adjunct to conventional breast MRI for improved positive predictive value. Am J Roentgenol 193: 1716–1722.
42. Goyon I, Weston J, Barnhill S, Vapnik V (2002) Gene selection for cancer classification using support vector machines. Machine learning 46: 309–422.
43. Saes Y, Inza I, Larrañaga P (2007) A review of feature selection techniques in bioinformatics. Bioinformatics 23: 2507–2517.
44. Akay MF (2009) Support vector machines combined with feature selection for breast cancer diagnosis. Expert Systems with Applications 36: 3240–3247.
45. Chen H, Yang B, Liu J, Liu D (2011) A support vector machine classifier with rough set-based feature selection for breast cancer diagnosis. Expert Systems with Applications 38: 9014–9022.
46. Aruna S, Rajajupalan DS, Nandakishore LV (2011) Knowledge-based analysis of various statistical tools in detecting breast cancer. Computer Science & Information Technology 2: 37–45.
47. Aci M, I ˙nan C, Avci M (2010) A hybrid classification method of k-nearest neighbor, Bayesian methods and genetic algorithm. Expert Systems with Applications 37: 5061–5067.
48. Yang C, Chuang I, Yang C (2010) IG-GA: a hybrid filter/wrapper method for feature selection of microarray data. Journal of Medical and Biological Engineering 30: 23–28.
49. Cai H, Cui C, Tian H, Zhang M, Li L (2012) A novel approach to segment and classify regional lymph nodes on computed tomography images. Computational and Mathematical Methods in Medicine 2012: 1–9.
50. Langer DL, Kwaat TH, Evano AJ, Trachtenberg J, Wilson BC, et al. (2009) Prostate cancer detection with multi-parametric MRI: Logistic regression analysis of quantitative T2, diffusion-weighted imaging, and dynamic contrast-enhanced MRI. Journal of Magnetic Resonance Imaging 30: 327–334.