Table: Results of the systematic search in PubMed and Web of Science of open source clinical studies published up to May 2017, where texture analysis has been used in the analysis of Dynamic Contract Enhanced Magnetic Resonance Images (DCE-MRI). Search terms were combinations of words derived from "texture analysis" (i.e. texture analysis, textural, texture descriptors, texture characteristic) AND "DCE-MRI". The time points where the texture analysis was used on each paper appears highlighted in the correspondent column.

Ref. no.	Sample size and type	Age range	Pathology studied	Contrast agent (type and dose)	MR Scanning sequences (includes temporal resolution)	Purpose for using texture analysis	Texture analysis	Other analyses
1	41 women (24 with malignant breast tumour and 17 benign)	Not specified	Breast cancer	Gd-DTPA	Sag T1-weighted spgr, 1 series pre-contrast & 3-8 series post-contrast, 90s temp. resol. (minimum); 1.5T or 3T	Tumour type classification (benign or malignant)	92 **pre-contrast** texture features, 92 **peak contrast** and 92 **kinetic**: gradient (from Gabor, Sobel and Kirsch filters), gray level (1^{st} order) and Haralick (2^{nd} order) features	Support Vector Machine and Prob. Boosting Tree classifiers
2	100 women with locally advanced breast cancer, undergoing chemotherapy	31-77 years (median age: 48 years old)	Breast cancer	Gd-based (0.05 mmol/kg) followed by 20mL saline flush. Injection time: 10 sec.	Sag T1-weighted spgr fat nulled, 10^{o} flip angle, 2 phases pre-contrast and 10 post-contrast, 33.6 sec. (ave) temp. resol.; 3T	Explore tumour responsiveness to chemotherapy	All Haralick features + cluster shade and cluster prominence **on 1-5 min post-contrast data.** Co-occurring values for 0^{o}, 45^{o}, 99^{o} and 135^{o} averaged.	Mann-Whitney U and t-tests using the textural features to explore effectiveness separating patient groups
3	18 patients (9M, 9F) with limb sarcomas	Median age: 54.3 years old	Limb cancer (Leg and arm tumours)	Gd-DTPA (0.1 mmol/kg) followed by N-saline flush	T1-, T2-weighted, DCE-MRI (T1-weighted, 10^{o} flip angle, 100 acquisitions, 2 sec. temp. resol.; 1.5T)	Quantify heterogeneity of tumour enhancement	Coherence (from Haralick) and fractal dimension (from Blanket method) on tumours. These are **computed from pharmacokinetic and heuristic model-based parametric maps** computed from the DCE-MRI data.	Spearman (correlation between textural features) Wilcoxon test (differences between textural features) and Mann-Whitney U (differences between 2 categories within the same feature)

4	234 women (85 with benign lesion and 149 malignant)	18-78 years (mean age: 46 years old)	Breast cancer	Gd-DTPA (0.1 mmol/kg) followed by 10 ml saline at 3 ml/s	Axial and sag T2-weighted fse, sag T1-weighted non-fat suppressed, DCE-MRI (T1-weighted fspgr fat suppressed, 1 pre-, 9 post-contrast acq., 270 sec. temp. resol.; 1.5T and 3T), DWI pre-contrast	Discriminate malignant from benign breast tumours at 1.5T and 3T	13 Haralick features on tumours. Texture done in addition to DWI and DCE-MRI from a static sequence **(not known if pre- or post-contrast)**	Diagnostic performance from morphology, kinetic, texture and ADC analyses using SVM, KNN, and random forest classifiers evaluated using ROC curves
5	102 women with malignant breast cancer	24-76 years (mean age (SD): 50.59 (9.95) years old)	Breast cancer	Gadobutrol (1.0mmol/mL), on a dose of 0.1 mmol/kg followed by 50 mL saline	DCE-MRI at 3T, 6 acquisitions at temporal resolution 40-50sec.	Classify tumours heterogeneity in ER, HER2 and TNBC status	8 GLCM features (energy, entropy, correlation, inverse diff moment, inertia, cluster shade, cluster prominence and Haralick's correlation) calculated from 13 directions in 3D **from the maximum enhancement ratio of DCE-MRI**	Tumour segmentation by region-crowing algorithm. Region-based, GLCM texture and shape features, and parameters of Tofts model extracted from segments of the tumour, determined by clustering the kinetic curves using fuzzy c-means.
6	65 women with breast cancer	31-74 years (mean age: 53.2 years old)	Breast cancer	2 types of gadolinium-based (0.1 mmol/kg)	3D T1-weighted fat-suppressed gradient-recalled echo-pulse, every 90-110 sec., 6 acquisitions; 1.5T	Differentiate: a) Estrogen receptor positive tumours from negative b) Tumours with viable lymph node metastases	22 gray level co-occurrence matrix, 11 gray level run length matrix and 76 local binary pattern histogram Fourier features **from both IE (initial enhancement) and PIE (post-initial enhancement) kinetic maps** of the tumours.	Multiparametric feature sets evaluated independently using 6 meta-classifiers: naïve Bayes, decision trees and support vector machine, each using correlation-based and wrapper-based feature subset selection

						after chemotherapy from tumours without nodal metastases		
7	121 women (77 malignant and 44 benign lesions)	21-85 years (mean age: 51.2 years old)	Breast cancer	Gd-DTPA (0.2 mmol/kg), flow rate of 2 ml/s followed by saline flush of 20 ml	3D T1-weighted spgr, 30^{o} flip angle, non-fat suppressed, one pre-contrast and 5 post-contrast series, 69 sec. temp.resol.; 1.5T	Investigate volumetric (3D) vs. 2D texture analysis approach to characterise breast cancer lesions	All Haralick features for 16, 32, 64 and 128 grey levels in 3D co-occurrence matrices. The texture analysis is performed on **the first post-contrast frame** of the DCE-MRI data	Diagnostic accuracy for each feature determined statistically. Bonferroni correction done afterwards.
8	19 patients (9 women, 10 men), 8 with Glioblastoma and 11 with Malignant Glioneuronal tumours	40-71 years (median age: 57 years old)	Brain cancer	Gd-DOTA (0.1 mmol/kg)	2D Sag T1-weighted fmpspgr 10^{o} and 90^{o} flip angle pre-contrast and 90^{o} post-contrast during 15 mins. , 28 sec. temp. resol.; 1.5T	Differentiate malignant glioneuronal tumours from glioblastomas	Features from 3 statistical texture analysis methods: gray-level histogram 1st order statistics, Haralick co-occurrence matrix, and run-length distribution matrix, **extracted from post-injection T1w images**. DCE-MRI complementary to texture analysis.	Mann-Whitney U test for group differentiation, principal component analysis and hierarchical ascendant classification done for each class of textural features
9	96 women with breast cancer	29-64 years old Mean ages: 48.8 years (training group, n=60) and 47.06 years (testing	Breast cancer	0.2 mmol/kg followed by a saline flush of 20 ml at same rate (2 ml/s)	3D fat-suppressed T1-weighted and fat-saturated T2-weighted, and 3 DCE-MRI series at intervals of 1.5 min, 2.5 min and 8.5 min, obtained at 1.5T	Investigate the role of features derived from breast DCE-MRI and incorporate clinical info. to predict molecular subtypes of breast cancer	45 texture features: contrast, correlation, energy, homogeneity and entropy **in pre-contrast, the 1st and 2nd post-contrast images** for the lesion and background parenchyma, all from a 3D GLCM.	5 morphologic features, 15 1st order statistical features, 29 dynamic features from the breast lesion and BPE, and 9 bilateral differences in background parenchymal area. Classification used evolutionary algo.

		group, n=36)						
10	98 women with breast cancer	31-77 years old. Mean age: 48 years			3T fat-nulled T1-weighted DCE-MRI: 2 pre-contrast and 10 post-contrast. Median temporal resol. 33.6 sec. (23.5 - 44.6 sec)	See whether Minkowski Functionals can be used to distinguish between cancer types before chemotherapy treatment, and whether a response to treatment can be predicted by an initial scan alone	Minkowski Functionals (MF) (area, perimeter and Euler value) from binary images created from **2nd or 3rd post-contrast phase**, used sets of rising thresholds to remove pixels.	Mann-Whitney-U compared mean MFs for each threshold -> 29 tests per patient subgroup. Change in means across threshold level described using polynomial fit to characterise the data. Logistic regression determined classif. performance.
11	60 women with triple-negative early-stage breast cancer receiving chemotherapy	Mean age: 46 years old	Breast cancer	Gd-DTPA (0.1 mmol/kg) at rate of 2 mL/s	Acquisition at 2 centres: 1)19 post-contrast acquisitions spaced 6-12 mins. 2) Median 5 post-contrast acquisitions spaced 1-5 mins. (Median temp. resol. 2 mins. 46 sec.)	Predict response to chemotherapy in early-stage breast cancer using heterogeneity measures from the grey level co-occurrence matrix obtained from DCE-MRI-derived lesion kinetic maps	31 features from the grey level co-occurrence matric pre- and post-chemotherapy. **Three time points were considered: 1) injection, 2) Either 110s or the first post-contrast image (whichever is later) and 3) Last image in series that was no more than 20min after injection.** Texture features were computed from kinetic maps of two classes: (a) empirical parameters (from the three time point rates of wash-in,	In addition to textural features, clinical/pathological/ genetic features and semantic morphological features were extracted. Feature selection by logistic regression (Lasso algorithm). Model performance assessed using ROC curves.

							wash-out and AUC between points 1 and 3; see Figure 2 in the paper) and (b) modelled pharmacokinetic parameters	
12	19 patients with head and neck squamous cell carcinoma (3M, 16F)	41-74 yrs. old, mean age 57 years	Head and neck squamous cell carcinoma	Gd-DTPA at a bolus of 0.1 mmol/kg and 2 cc/s, followed by saline flush	T1/T2-weighted and DCE-MRI: 2D-SPGR TR=7.8ms, TE=1.9ms, 50-60 phases, 30^{o} flip angle, temporal resolution = 6 sec ; 1.5T	To investigate the merits of texture analysis on parametric maps derived from pharmacokinetic modeling with DCE-MRI as markers for the prediction of treatment response in patients with head and neck squamous cell carcinoma	Texture analysis on parametric maps of K^{trans} and v_e (from Tofts model) at the tumor's central slice. Textural features: Haralick Energy and Homgeneity (from GLCM)	Lilliefors test used to test the normality of all DCE-MRI-derived measures. Differences in texture and parametric maps between pre-treatment and intra-treatment groups analysed with t- and Mann-Whitney U tests. Prediction capacity determined with logistic regression.
13	8 women with breast tumours	Not specified	Breast cancer	Gd-chelate (0.2 mL/kg), constant bolus injection during 7 sec.	T1-weighted gradient echo 20^{o} flip angle, 6 acquisitions spaced 120 sec.; 1.5T	Investigate feasibility of using texture analysis to detect malignant tumours	Haralick features determined from pseudoimages generated **from 3 parameters from the 2-compartment model for contrast agent exchange (A, k_{ep} and k_{el})**	Textural parameters input to a feedforward neural network classifier. True positive and negative fractions used to compare gold standard radiological results with results from classifier

14	82 biopsy proven (51 malignant, 31 benign) from 74 women	19 to 82 years old	Breast cancer	0.2 mmol kg^{-1} gadopentetate dimeglumine followed by a 10 ml saline solution flush	Coronal 3D, 1 series before and 5 series post contrast (time interval of 60s). T1W Spoiled Gradient Echo sequence. Repetition time (TR) 8.1 ms, echo time (TE) 4ms; 1.5T	Discriminating malignant from benign lesions	14 features from GLCM **of three parametric maps: Initial Enhancement, Post-initial enhancement and Signal Enhancement Ratio**.	Lesion enhancement kinetic parametric maps (Initial Enhancement, IE; Post-Initiail Enhancement, PIE and Signal Enhancement Ratio, SER). Least squares minimum distance classifier
15	71 lesions: 43 malignant and 28 benign. Number of women not specified	Not specified	Breast cancer	Not specified (the abstract does not specify anything about DCE)	Not specified	Tumour classification (discriminating benign and malignant)	8 morphologic parameters and 10 GLCM texture features	Artificial Neural Network. ROC analysis. Feature selection
16	39 women: 19 malignant breast cancer, 17 benign and 3 normal	Not specified	Breast cancer	Gd admin over 10 sec	DCE-MRI with fat suppressed 3DT1W 10^{o} flip angle; Conventional structural MRI T2W fast spin echo, DWI-EPI, and short T1 inversion recovery; 3T	To investigate whether differences in composition/texture and vascularity of normal, benign and malignant breasts may serve as potential indicators of the disease	Two families of features were extracted: 1) vessel-based morphological and textural features from segmented images; 2) textural features from the whole breast region: 1^{st} order stats (mean intensity value, foreground /background intensity ratio, SD, skewness and kurtosis of intensities, volume, vessel density, number of bifurcations and terminals), 14 Haralick features from GLCM, 5 Galloway features from the	Kruskal-Wallis and Wilcoxon non-parametric tests for group comparison, and ROC with logistic regression to test predictive ability of features

							run-length matrix, 6 Tamura features and 24 frequency features from multi-scale histograms at 3, 5, 7 and 9 bins.	
17	23 prostate cancer patients	Not specified	Prostate cancer	bolus injection (0.1 mmol/kg; rate: 2 mL/s) followed by a 20-mL normal saline flush	T2W, DWI and 3D fast low-angle shot sequence (time-resolved imaging with stochastic trajectories) for the DCE-MRI (TR/TE: 3.85/1.42 ms; flip angle: 12°) pre-contrast T1W using four variable flip angles (2°, 5°, 10°, and 20°), followed by 70 dynamic scans at 4.22 s temporal resolution; 3T	To evaluate the diagnostic relevance of T2W-MRI-derived textural features relative to quantitative physiological parameters derived from DWI and DCE-MRI in Gleason score (GS) 3+4 and 4+3 prostate cancers	Haralick Textural features [angular second moment (ASM), contrast, correlation, entropy], apparent diffusion coefficient (ADC), and DCE pharmacokinetic parameters (K^{trans} and V_e) calculated from index tumours delineated on the T2W, DW, and DCE images	Point-biserial (r_{pb}) and Spearman correlation coefficients (ρ) to explore relation between textural features and GS, ADC, K^{trans}, and V_e. Differences between GS 3+4 and GS 4+3 cancers determined with two-tailed Mann-Whitney U tests
18	23 DCE-MRI parameter maps: 9 low grade gliomas and 14 high grade gliomas	Adults (age not specified)	Glioma	3ml at 15 ml/sec of Gd-DTPA-BMA. Dose: 0.1 mmol/kg of body weight	T1w; 3T	One of the experiments was to differentiate low-grade and high-grade gliomas. The other was with simulated data	Fractal dimensions **from DCE-MRI parameter maps**	t-test
19	70 clinical cases: 39 probably	Not specified	Breast cancer	0.1 mmol/kg of	T1w in prone position before and after contrast	Classification of suspicious breast masses	Multifractal scaling exponent for each clinical	ROC analysis

	malignant and biopsied and 31 probably benign and nonbiopsed			Gadopentetate dimeglumine (Gd-DTPA).	injection. Five bilateral axial acquisition series were taken at intervals of 111s. 3T. The time points considered for 3TP were 0s, 111s and 444s.		case and log-cumulants reflecting multifractal information related with texture. **The first post-contrast images acquired after contrast arrival were used for the multifractal analysis.**	
20	58 patients	35-82 (median= 54)	Breast cancer	0.1 mmol/kg body weight of gadoliniumbased contrast agent at 2 mL/s, followed by a 20 mL saline flush	T1w with temporal resolution of 1 min acquired on 3T. 1 pre-contrast and 7 post-contrast images with a temporal resolution of 1 min	Predict the clinical and pathological response to neoadjuvant chemotherapy (NAC) in patients with locally advanced breast cancer (LABC) before NAC is started	16 GLCM features **at each non-subtracted post-contrast time point**	Kruskal-Wallis test and Mann-whitney U-test. ROC analysis
21	81 patients with locally advanced cervical cancer: 49 currently free of disease and 32 relapsed	32-85 (median= 57)	Cervical cancer	Gd-DTPA with a dose of 0.1 mmol/kg body weight followed by saline solution flush	T1w and T2w prior to treatment. DCE-MRI with axial T1w; 1 series pre-contrast and 13 series post-contrast during 5 minutes (first 11 series with sampling interval of 15 sec and the other two with	Predict if treatment outcome on patients with cervical cancer can be predicted from parameters of the Brix pharmacokinetic model derived DCE-MRI	First-order (21 features). Contrast, correlation, energy and homogeneity from GLCM. Both first-order statistics and GLCM-based features are computed **from each Brix model pharmacokinetic parameter maps (A, k_{ep} and k_{el})**	Pharmacokinetic modelling. Brix parametric maps. Feature selection. Support vector machines. Leave-one-out cross validation. ANOVA and Tukey's HSD tests

					sampling interval of 1 min); 1.5T			
22	21 in vivo endorectal MR images from 6 patient datasets.	Not specified	Prostate cancer	0.1 mmol/kg of body weight of gadopentetate dimeglumine	T2W. The DCE-MRI were acquired during and after contrast agent injection using 3-dimensional Gradient Echo sequence with temporal resolution of 1 min 35 sec; 7 time points; 3T	Segmentation, registration and detection of prostate cancer	Nonlinear dimensionality reduction (using Locally-linear embedding) of pixel intensities, **done at each time point**	Active Shape Model; Affine registration; K-means clustering
23	20 rabbits with cholesterol diet and endothelial denudation; 30 extracted segments: 16 contained thrombus (vulnerable) and 14 did not (stable)	N/A	Athero-sclerotic plaques; preclinical (rabbits)	Magnevist 0.01 mmol/kg	2 image modalities of 2D axial T1wBB (T1-weighted black blood) images and DCE-MRI 2D axial before and every 2-3 minutes after injection of contrast agent for additional 7 time points; 3T	Distinguishing vulnerable versus stable atherosclerotic plaques on DCE-MRI using a rabbit model of atherothrombosis	352 voxel-wise features: 192 Gabor, 36 Kirsch, 12 Sobel, 52 Haralick and 60 first-order textural features from each voxel over the course of contrast uptake (i.e. **on each time point**)	Minimum-redundancy-maximum-relevance (mRMR) feature selection. Random forest classifier.
24	96 ER-positive breast lesions with low (<18, *N* = 55) and high (>30,	Not specified	Breast cancer	Gd-DTPA of 0.1 mmol/kg at 4cc/sec for 5-10 min.	Multiplanar T1W, T2W, DCE-MRI at 1.5T	To identify computer extracted imaging features for estrogen receptor (ER)-	Each lesion was characterized via 6 shape features, 3 pharmacokinetics, 4 enhancement kinetics, 4 intensity kinetics, 148 textural kinetics, 5 dynamic	The extracted features were evaluated by a linear discriminant analysis (LDA) classifier in terms of their ability to distinguish low and high Onco*type*DX risk

	N = 41) Onco*type*DX recurrence scores					positive breast DCE-MRI that are correlated with the low and high Onco*type*DX risk categories	histogram of oriented gradient (DHoG), and 6 dynamic local binary pattern (DLBP) features.	categories. Classification performance evaluated by area under the ROC curve.
25	99 women with breast cancer (132 lesions: 63 benign and 69 malignant)	mean age 53.24 ± 9. 82 years (range 32 to 85 years)	Breast cancer	0.5 mmol/ml, gadodiamide or gadopentetate dimeglumine, with a bolus of 4ml/s at 5th acquisition	DCE-MRI: 35 acquisitions in 30 sec 3D FSGR, flip angle 12^{o}; 1.5T	Tumour segmentation and classification	14 Haralick textural features from the images of the **fourth phase of DCE-MRI before contrast**	Thresholding, shape features, and pharmacokinetic parameters from Tofts model. Logistic regression used for classification. Validation with Mann-Whitney U, accuracy, PPV, sensitivity, specificity and ROC curves.
26	63 benign lesions and 69 malignant lesions in 99 women	From 32 to 85 years old (mean 53.24)	Breast cancer	Gadodiamide, 0.5 mmol/ml or gadopentetate dimeglumine. Flow rate of 4 ml/s at the 5th acquisition	56 slices each acquisition (total: 35 acquisitions) using a fat suppressed 3-D fast spoiled gradient echo (FSGR) sequence; 1.5T;	Breast lesion classification (malignant/benign)	3D shape features and 3D texture features based on the GLCM, on a segmented tumour. **For segmentation, the kinetic and AUC colour maps combined were used**	3D Shape features (Compactness, margin and ellipsoid fitting); kinetic curve characteristics; binary logistic regression; leave-one-out cross-validation; Kolmogorov-Smirnoff and t-test or Mann-Whitney U test; ROC analysis
27	6 women: 4 malignant invasive ductal carcinoma	Not specified	Breast cancer	Gd-BOPTA, 0.2 mL/kg bodyweight during 7 seconds.	64 coronal slices, T1-weighted gradient echo; 1.5T; 6 volumes per dataset were	Voxel classification as malignant/non-malignant tissue	4D co-occurrence –based texture analysis: 14 Haralick features from GLCM with directions (0,0,0,1) (the 4th dimension	No registration used; Neural Network classifier; ROC analysis

	from 4 women, and 4 benign fibrocystic lesion from 2 women				acquired at 6 different time points: The first volume set was acquired to establish baseline intensity, and another five volume scans were taken 120 seconds apart		is the time). Thus, assessing variations in image brightness between the same voxel location **at different times (post-contrast).**	
28	35 women diagnosed with stage II/III breast cancer	Not specified	Breast cancer	gadopentetate dimeglumine, Gd-diethyl-enetriamine pentaacetic acid at 0.1 mmol/kg, delivered at 2 mL/sec after 3rd acquisition	DCE-MRI with TR = 7.9 msec, TE = 4.6 msec, and flip angle = 20°; at 3T	Predict treatment response	4 Haralick texture features (from the GLCM) extracted within each tumor subregion. The change in texture features in each tumor subregion **between pre- and during-neoadjuvant chemotherapy (NAC)** was used to predict pathological complete response after NAC.	Tumour segmentation by thresholding, temporal dimensionality reduction via PCA, intratumour partitioning using k-means clustering, evaluation of predictors using ROC curve analysis and AUC from univariate logistic regression models.
29	210 women with breast cancer from two cohorts	Mean age: 59.2 ± 11.0 years and 54.0 ± 11.5 years	Breast cancer	Gd-based contrast agent, dose of 0.1 mmol/kg and flushed with 20 mL saline.	T1W with fat-suppressed GRE flip angle 10°, at 1.5T and 3T. MRI acquired at 4 time points: 1 immediately before contrast injection, 2-4 at 1 minute, 2 minutes, and 6	To determine DCE-MRI characteristics of the breast tumor and background parenchyma can distinguish molecular subtypes (ie, luminal A/B or	8 tumor morphological features, 12 tumor texture features (4 Haralick features: entropy, uniformity, dissimilarity and cluster shade, **at early enhance, late enhance and from signal enhancement ratio**, from GLCM), 3 functional tumor volume features, 6 parenchymal	Tumour and background manually segmented. Logistic regression models combined with Least Absolute Shrinkage and Selection Operator for feature selection to avoid overfitting. Validation using Mann-

					minutes after injection.	basal) of breast cancer	enhancement features, and 6 tumor-surrounding parenchymal enhancement features.	Whitney U tests, ROC and AUC analyses.
30	20 tumours from 18 women: 4 malignant cancer, 6 invasive ductal carcinoma, 10 inflammatory breast cancers	39-59 years old; mean=48 years	Breast cancer	Gadolinium (0.3 cc/sec at a temporal resolution of 30 s)	Modality not specified. Just used the post-contrast images; acquired at 1.5T.	Breast cancer classification: Pixel-by-pixel classification technique for tumour evaluation.	For each pixel, textures of a block of 8x8 pixels are are characterised based on: Histogram statistics (6 features), GLCM (9 features) and run-length matrices (11 features). 32 intensity bins for GLCM and run-length. Wavelet features: Mean and std from 3 wavelet subbands (low and high pass). **Each textural feature forms a temporal sequence in DCE-MRI**	Segmentation of breast region using active contour model. Feature selection. Support Vector Machines (SVM). ROC analysis

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