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# A Novel Framework for Breast Tumor Segmentation and Classification Using Extreme Machine Learning

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***Abstract*: A breast tumor examination can help to detect the tumor in the early stages, which is meaningful for the cure. The medical image examination in digital mammography is the most effective method of the breast cancer detection. Computer-aided diagnosis (CAD) on breast tumor detection will provide a confirmation for the radiologists in detecting the suspicious regions in images and also improve accuracy and efficiency. This paper builds on prior work looking at neo adjuvant response to query whether baseline pharmacokinetic (PK) imaging heterogeneity can be used to predict prognosis. The Entire process is carried out in two phases: Segmentation and Classification of the breast tumor. In segmentation process, the tumor pixels are partitioned into groups that act similarly based on PK heterogeneity measures. Wavelet kinetic features are then extracted within each partitioned sub region to obtain the spatiotemporal patterns of the wavelet coefficients and contrast agent uptake. We extract localized spatiotemporal features within the obtained tumor pixel partitions, based on specific heterogeneity properties. During Classification Process, The features of the tumor are extracted, and input into ELM, as well as the judgment of radiologists which acts as the standard indicative of the classification, then the training of ELM is finished.**

***Keywords:* Breast cancer recurrence prediction, breast dynamic contrast-enhanced magnetic resonance imaging (DCEMRI),feature extraction, gene expression, partitioning, ELM.**

## 1. INTRODUCTION

Breast cancer is second most commonly diagnosed cancer worldwide. In order to find the cure it is necessary to quickly diagnose the disease accurately and treat it based on the kind of symptoms appeared. Breast cancer has several classifications, which may help to determine the best treatment. The most important of these classifications are binary classification, either benign or malignant. If the cancer is in benign stage, less invasive and risk of treatments is used than for malignant stage .The reason being the chances of survival of patient is high; it is not beneficial to increase the speed of recovery at the risk of introducing potentially life threatening side effects caused by aggressive treatment. On the other hand a patient with malignant cancer is not so concerned about the kind of treatment or side effect of the treatment. The main cause of breast cancer is when a single cell or group of cells escapes from the usual controls, that regulate cellular growth and begins to multiply and spread. This activity may result in a mass, tumor or neoplasm. Many masses are benign that means the abnormal growth is mainly restricted to a circumscribed, single and expanding mass of cells .Some tumors are malignant that means the abnormal growth invades the surrounding tissues and that may metastasize or spread to remote areas of the body . The benign masses may leads to complications where as Malignant tumors are serious cancer. The majority of breast tumors will have metastasized before reaching a tangible size. So far, a various numbers of imaging techniques are discovered for breast cancer detection in tissue level.

## 2. RELATED WORK

Breast tumors are heterogeneous lesions. Intra-tumor heterogeneity presents a major challenge for cancer diagnosis and treatment Few studies have worked on capturing tumor heterogeneity from imaging In this work we capture tumor heterogeneity by partitioning tumor pixels into sub regions and extracting heterogeneity wavelet kinetic (Het Wave) features from breast dynamic contrast-enhanced magnetic resonance imaging (DCE-MRI) to obtain the spatiotemporal patterns of the wavelet coefficients and contrast agent uptake from each partition. Stefan et al. urges a framework for brain tissue segmentation. They developed fully automatic method that combines Support Vector Machine classification using multispectral intensities and textures with subsequent hierarchical regularization based on Conditional Random Fields (CRF).Features are extracted from the multispectral imaging data. It use the first order texture features that can be computed fast and easily from small patches around each voxel in all four modalities. Classification is done using a soft-margin SVM classifier. The appealing property of SVMs is that they offer the possibility to use a kernel function for transforming the data into a higher-dimensional feature space, where the data can be linearly separated efficiently with a maximum margin. Slack variables are used for soft-margin classification. Parameter selection for the SVM classifier with a radial basis function (RBF) kernel is done using grid-based cross-validation on the training data. In order to extend the inherently binary SVM classifier to a multiclass problem, it use a one-against-one voting strategy. The given SVM classification is based on the Lib SVM implementation. Regularization is done in two different stages using a CRF method. Then a second-order CRF with two energy terms is used. The unary potentials can be calculated directly from the voxel-wise output produced by the SVM classifier. The smoothness energy is computed depending on the neighboring voxels. The label distance function is used to penalize adjacencies of necrotic or active tumor regions with healthy tissues more strongly because these adjacencies are less likely to occur. After the first coarse classification into tumor and healthy tissues, a strong 3Dregularization is employed using a von Neumann neighborhood. In a second stage, regularization is applied on the image, which has been sub classified into the different tumor and healthy sub regions. Then it employs a recent optimization algorithm which is based on linear programming via graph-cuts and primal-dual decomposition. For Brain Tumor Image Analysis, the images undergo a preprocessing pipeline. First, the four modalities are registered with the help of a rigid registration and mutual information metric. Next, only the brain region is extracted from the images using a fully-automatic, customized skull-stripping algorithm. Subsequently, noise is removed with an edge-preserving smoothing filter and the bias field is corrected. The preprocessing is completely integrated with the SVM classification and CRF regularization components using the Insight Toolkit for Segmentation and Registration (ITK).The benefit is it increases robustness and speed. It provides great computational efficiency. It improves the overlap with the ground truth significantly.

Feature selection is a process commonly used in machine learning, wherein a subset of the features available from the data is selected for application of a learning algorithm. In forward selection, it use a simple ranking based feature selection criterion, a two –tailed t-test, which measures the significance of a difference of means between two distributions, and therefore evaluates the discriminative power of each individual feature in separating two classes. It use this feature ranking method to select the more discriminative feature, e.g.by applying a cut-off ratio and then apply a feature subset selection method on the reduced feature space.In Backward Selection, it start with all the variables and remove them one by one, at each step removing the one that decreases the error the most, until any further removal increases the error significantly. To reduce over fitting, the error referred to above is the error on a validation set that is distinct from the training set. The support vector machine recursive feature elimination algorithm is applied to find a subset of features that optimizes the performance of the classifier. This algorithm determines the ranking of the features based on a backward sequential selection method that remove one feature at a time.Linear Discriminant Analysis (LDA) technique is used for data classification and dimensionality reduction.

In order to detect the tumor it use a histogram-based FPCM. It classify the extracted brain into five classes, cerebro spinal fluid (CSF), white matter (WM), gray matter (GM),tumor and background. To obtain the initial values of the class centers, it use the results of the histogram analysis in the brain extraction step. Because of some classification errors, there are undesired additional voxels in the tumor class. To remove the semi classified components, several binary morphological operations are applied to the tumor class. An opening operation is first used to disconnect the components. Then it select the largest connected component, which proved to always correspond to the tumor, even if it has a small size.

Shan et al. introduce a new method for brain MRI segmentation. They provide a robust segmentation technique, called as improved fuzzy c-means clustering (IFCM). The membership value of FCM decides the segmentation results, and the membership value is determined by the similarity measurement.In FCM, the similarity measurement is a measure of the difference between the intensity of a pixel and the cluster center, and has no resistance to noise. During clustering, each

pixel attempts to attract its neighboring pixels toward its own cluster. This neighborhood attraction depends on two factors; the pixel intensities or feature attraction, and the spatial position of the neighbors or distance attraction, which also depends on the neighborhood structure. IFCM considers the neighborhood attraction in similarity measurement directly. The two parameters $\lambda$ and $\xi$ of magnitude between 0 to 1, adjust the degree of the two neighborhood attractions.

1. Apply three preprocessing techniques to the image, which are median filter, histogram normalization and histogram equalization.

2. Determine the threshold value.

3. Click mouse in the region of interest.

4. Choose N × N neighbor hood.

5. Set the initial value for Total of pixels and grey level for all pixels in the region with original grey level value of the initial seed pixel.

6. Calculate the mean value and standard deviation of the N × N neighborhood.

7. Grow the seed pixels to its neighbour's pixels. Compare the grey level of the seed pixel with its neighbour's pixel. Include the neighbour pixel into the region.

8. If the neighbour pixel is included into the region:

a. Add one to region the in pixels of Total value.

b. Add original grey level of the neighbour pixel to Total of grey level for all pixels in the region value.

9. Set the neighbour pixel as a new seed pixel.

10. Repeat Step (6) to (9) until all pixels have been considered to be grown or the pixel cannot be grown anymore.

11. Calculate the value of the size and grey level of the region.

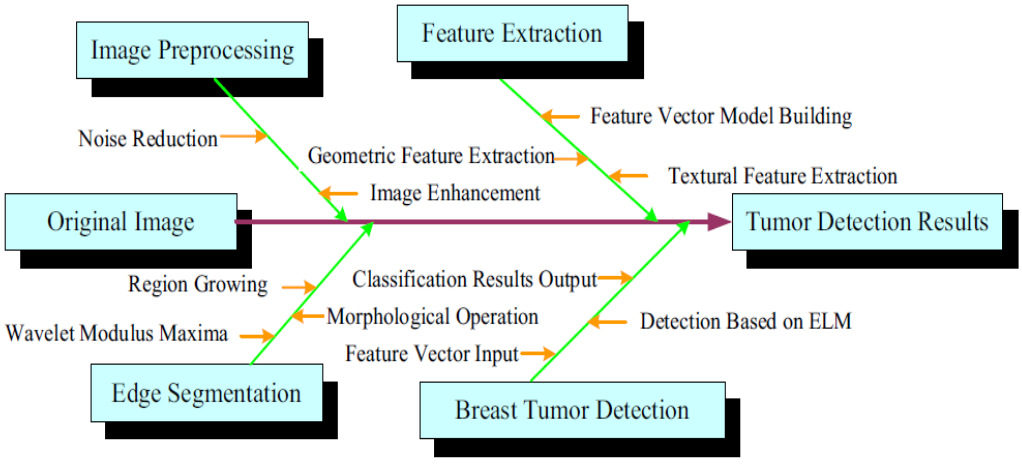
## 3. PROPOSED SYSTEM

In this paper ,we present a novel breast tumor detection method based on ELM. After doing then noise reduction and the enhancement in digital mammography, we segment the edge of the tumor.

The features of the tumor are extracted, and input into ELM, as well as the judgment of radiologists which acts as the zstandard indicative of the classification, then the training of ELM is finished. As a result, we can detect the existence of a tumor in the images and assist radiologists in examining images.

**A. Breast tumor detection based on ELM:**

Framework overview



In this paper there are 4 steps of tumor detection in digital mammography

Image preprocessing,

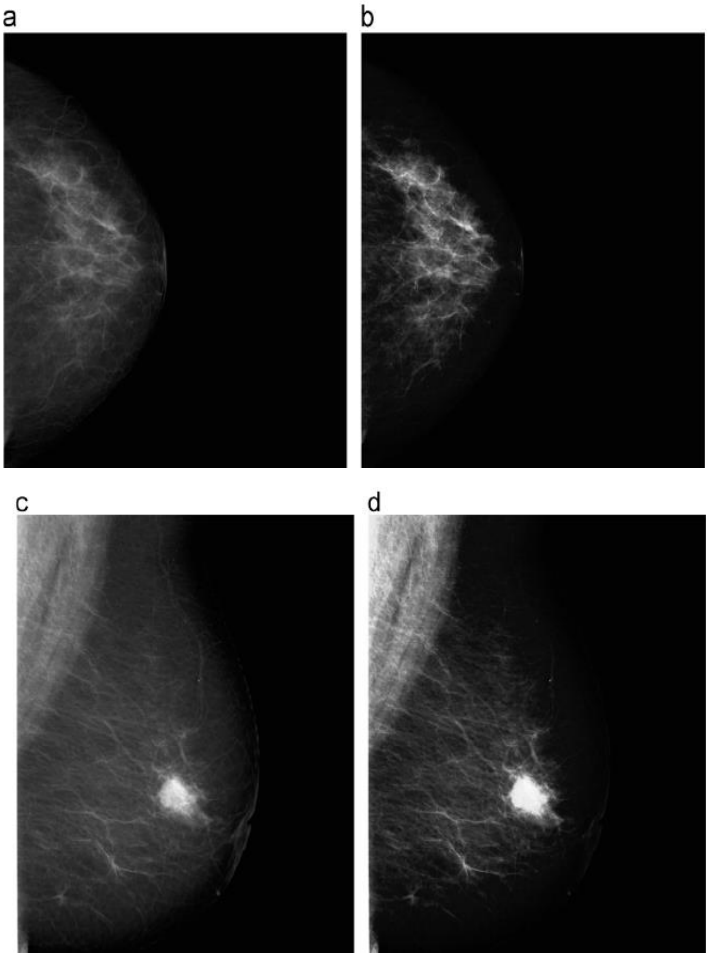
Edge segmentation,

Feature extraction

Breast tumor detection based on ELM.

**B. Image preprocessing:**

Image preprocessing includes two steps, noise reduction and enhancement of image. First, a median filter is used for noise reduction ,and contrast enhancement of the digital mammography in data preprocessing




**Contrast images of before and after preprocessing.**

(a)Original image without a tumor, (b) after preprocessing of(a), (c)original image with a tumor and (d)after preprocessing of (c).

**C. Edge segmentation:**

**(**We segment the edge of tumor) In this paper, the wavelet transformation of local modulus maxima (WMM)edge detection morphological operation and the region growing algorithm are used to implement the effective edge segmentation of a breast tumor. After the segmentation based on wavelet modulus maxima algorithm ,morphological operation and region growing algorithm have been performed on the image.

**D. Feature extraction:**

It is the process of defining a set of features, or image characteristics. Here, I use two different feature extraction methods Geometric feature extraction Texture feature extraction Geometric features such as shape, size edge. Texture features such

as reverse gap, contrast, Energy .Next, methods of wavelet modulus maxima transform, morphological operation and region growth are used for the breast tumor edge segmentation. Then, five textural features and Five morphological features are extracted. Finally, an ELM classifier is used to detect the breast tumor.

**E. Digital mammography:**

Digital mammography is a specialized form of mammography that uses digital receptors and computers instead of x-ray film to help examine breast tissue for breast cancer.

**F. Computer aided diagnosis:**

In radiology, **computer-aided detection (CADe)**, also called **computer-aided diagnosis (CADx)**, are procedures in medicine that assist doctors in the interpretation of medical images.

**G. Median filter:**

The **median filter** is a nonlinear digital filtering technique. And it perform noise reduction on an image or signal. Median filtering is very widely used in digital image processing because, it preserves edges while removing noise

**H. Wavelet transformation of local modulus maxima(WMM):**

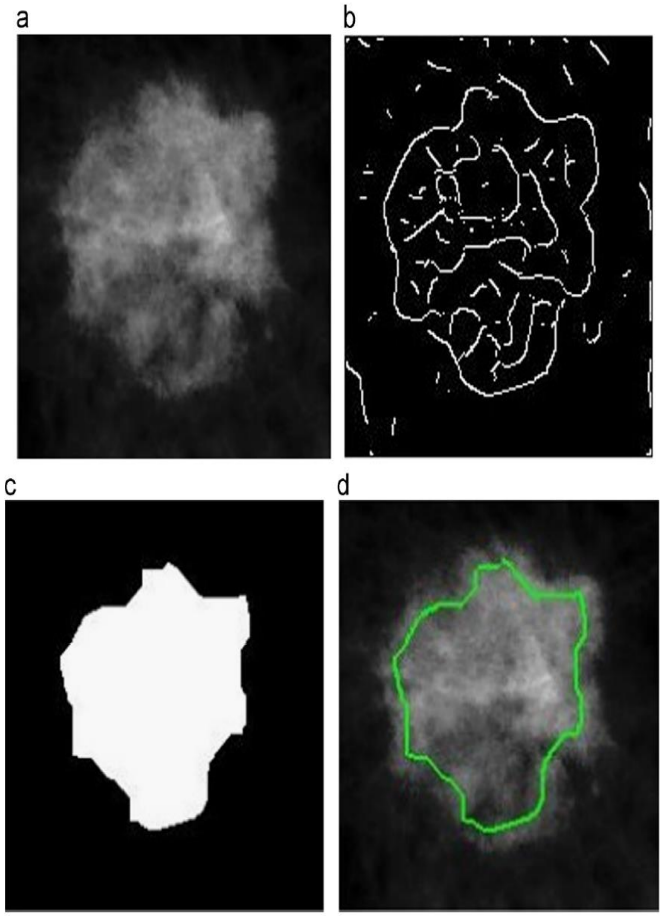
The wavelet transform modulus maxima (WTMM) is a method for detecting the fractal dimension of a signal.

**Morphological operation:**

Morphological operation is used to extract image components for representation of region shape Once segmentation is complete, morphological operations can be used to remove imperfections in the segmented image and provide information on the form and structure of the image

**Region growing algorithm:**

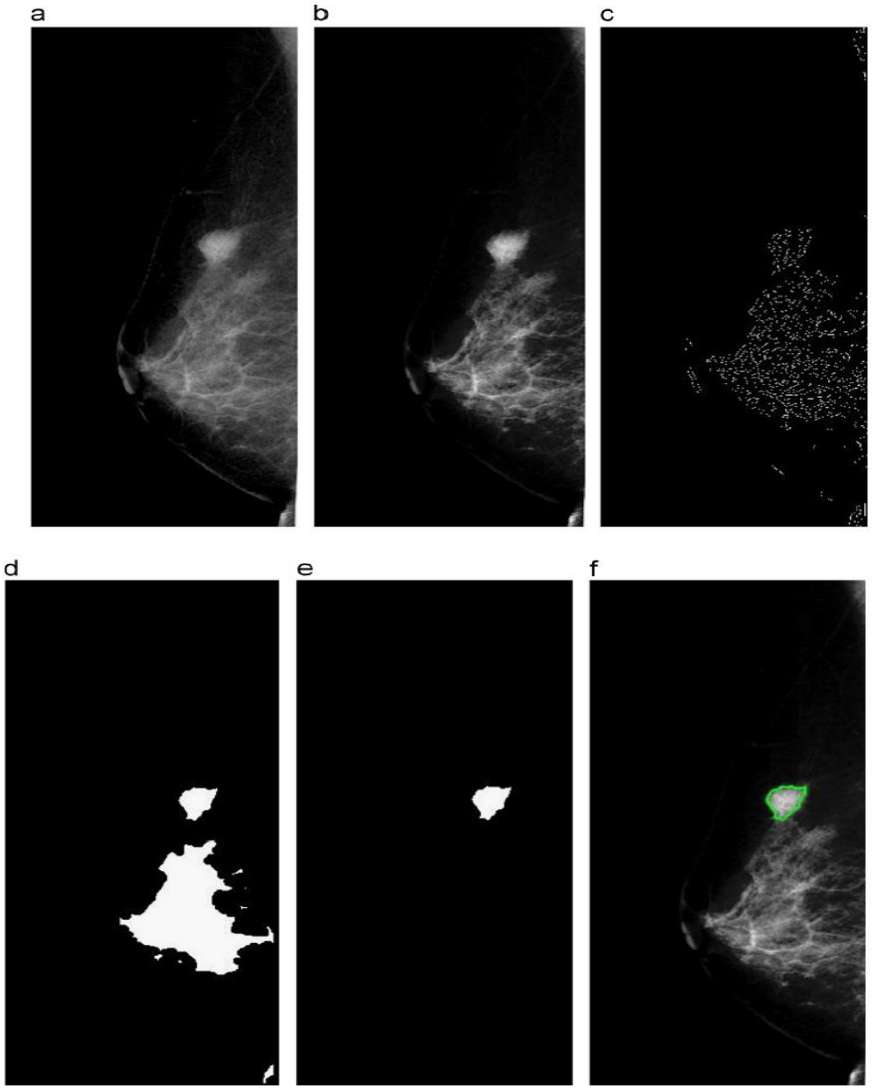
It is used to group pixels or sub regions into larger regions. It is a simple region-based image segmentation method.




**Example of breast tumor segmentation. (a)Region of interest, (b) WMM,(c) morphological operation and (d) region growing**

**Extreme learning machine (ELM):**

Extreme learning machine (ELM) is a new learning algorithm it is used to detect the breast tumor. ELM algorithm has a excellent generalization performance , rapid training speed , faster learning time with a higher training and testing accuracy and little human intervention. Extreme learning machine used in many fields such as text classification, image recognition , mobile object management and bioinformatics .




**Effect of image after pre processing and segmentation. (a) Digital mammography, (b) pre processing, (c) WMM,(d ) morphological,(e) region growing and (f) edge of tumor**

## 4. METHODOLOGY

This paper builds on prior work looking at neo adjuvant response to query whether baseline pharmacokinetic (PK) imaging heterogeneity can be used to predict prognosis. We introduce a methodology to characterize intra tumor PK heterogeneity from breast DCE-MRI data. Our method, which builds up honour previous work [17], [18], uses a two-step approach: first, the tumor pixels are partitioned into groups that act similarly based on PK heterogeneity measures. Wavelet kinetic features are then extracted within each partitioned sub region to obtain the spatiotemporal patterns of the wavelet coefficients and contrast agent uptake.

**A. Pharmacokinetic Heterogeneity-Based Partitioning:**

In DCE-MRI, a region of interest (ROI) or individual voxel can have a characteristic signal intensity time course which is related to the contrast agent concentration [19]. To model the uptake of the contrast agent by the tissue, several PK models have been proposed based on compartmental modeling (CM), using the on ROI and pixel-wise scales [4], [20]–[22].

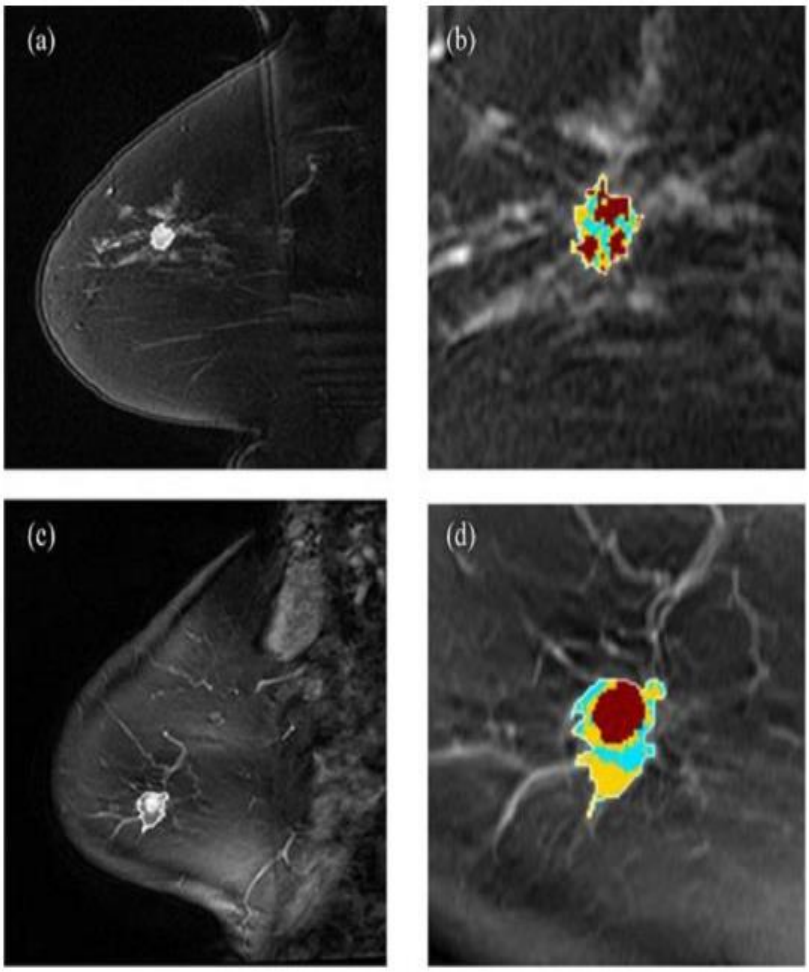



**Fig First post-contrast breast DCE-MR images (first column) and corresponding PK heterogeneity partitioning (second column; teal, gold, and darkred partitions represent low, medium, and high maximum first contrast uptake)for (a), (b) low recurrence risk and (c), (d) high recurrence risk tumor examples.**

**B. Heterogeneity Wavelet Kinetic Features:**

After obtaining the tumor partitions as described earlier, we use the wavelet transform [30] to characterize the spatial frequency information. In principal, different wavelet families (i.e.,bases) can be used for this purpose. Here, we have used the Daubechies 2 ("db2") as our primary wavelet family, which is shown to have better performance than other wavelet families. Assume the pre- and post-contrast images are defined as It (t=1represents the pre-contrast while t=2,3,.., Q correspond to the post-contrast images). Therefore, approximate, CtL(k), and detail coefficients, Dt ,sL(k), are obtained as follows

$$C_L^t(k) = I_t \cdot \Phi_{L,k}$$
$$D_L^{t,s}(k) = I_t \cdot \psi_{L,k}^s.$$
$$\mu_{cA,L}(i,t) = \frac{\sum_{k=1}^{N} C_L^t(k)\,\delta(M_k = i)}{\sum_{k=1}^{N} \delta(M_k = i)}$$
$$\mu_{cH,L}(i,t) = \frac{\sum_{k=1}^{N} D_L^{t,H}(k)\,\delta(M_k = i)}{\sum_{k=1}^{N} \delta(M_k = i)}$$

Low (first row) and high (third row) recurrent tumor contrast images and the corresponding wavelet images from the first post-contrast DCE-MRI scan (second and fourth rows); (a)–(d), pre- and post-contrast images of the lesion; (e) approximate wavelet coefficients at DP1; (f) horizontal wavelet coefficients at DP1; (g) vertical wavelet coefficients at DP1; (h) diagonal wavelet coefficients at DP2; (i)–(p) are similar to the previous description but for a tumor of high risk of recurrence.

$$\sigma^2_{cA,L}(i,t) = \frac{\sum_{k=1}^{N}(C_L^t(k) - \mu_{cA,L}(i,t))^2 \delta(M_k = i)}{\sum_{k=1}^{N}\delta(M_k = i)} \quad (11)$$

$$\sigma^2_{cH,L}(i,t) = \frac{\sum_{k=1}^{N}(D_L^{t,H}(k) - \mu_{cH,L}(i,t))^2 \delta(M_k = i)}{\sum_{k=1}^{N}\delta(M_k = i)}. \quad (12)$$

The mean and variance of the pre- and post-contrast images (It) within each partition are also obtained:

$$\mu_I(i,t) = \frac{\sum_{k=1}^{N} I_t(k)\,\delta(M_k = i)}{\sum_{k=1}^{N}\delta(M_k = i)} \quad (13)$$

$$\sigma_I^2(i,t) = \frac{\sum_{k=1}^{N}(I_t(k) - \mu_I(i,t))^2\,\delta(M_k = i)}{\sum_{k=1}^{N}\delta(M_k = i)}. \quad (14)$$

In this study, we used three heterogeneity partitions (p = 3),the mean and variance as statistic operations (s = 2), and two wavelet decomposition levels (d = 2). As a result, our final HetWave feature vector consists of 54 features.

**C. Dataset:**

Breast DCE-MRI sagittal scans of 56 women diagnosed with invasive breast cancer were collected at our institution during2007–2010, and retrospectively analyzed per HIPAA and IRB approval. These women had estrogen receptor positive and node negative tumors. The women were imaged prone in a 1.5T scanner (GE LX echo, GE Healthcare, or Siemens Sonata, Siemens);matrix size: 512 × 512; slice thickness: 2.4–4.4 mm; flip angle:25° or 30°, and T1-weighted.

**Block diagram of the Het Wave feature extraction based on tumor heterogeneity partitioning and recurrence risk classification:**

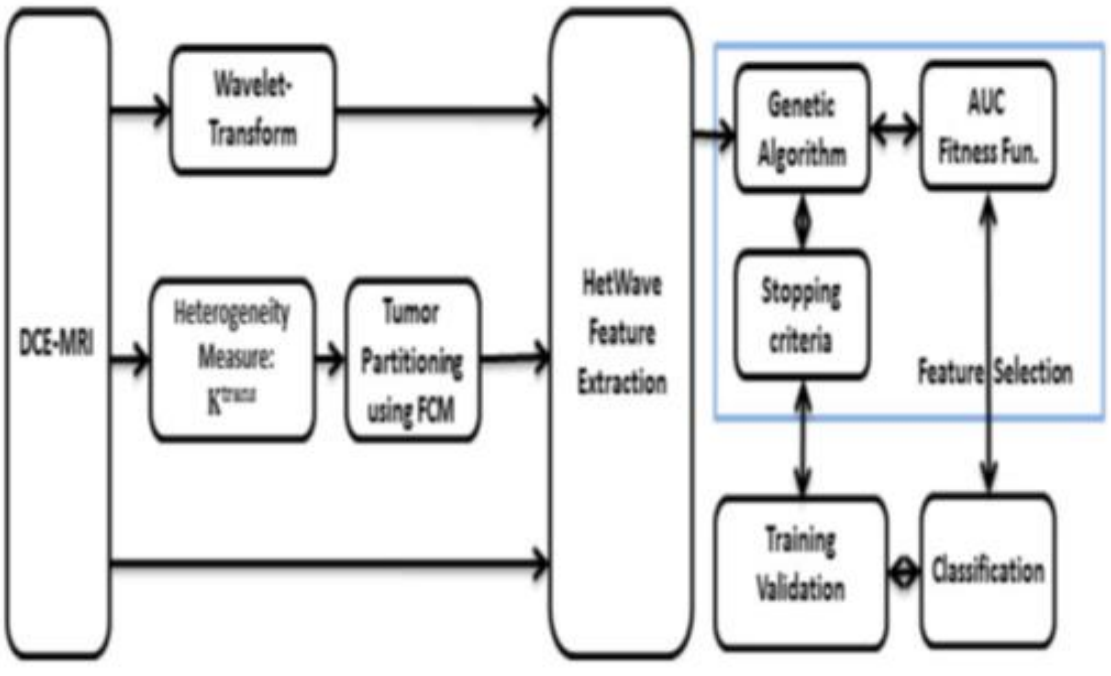


TABLE I
DCE-MRI STANDARD FEATURES USED FOR COMPARISON

| | |
|---|---|
| Kinetic [5], [14] [6] | Peak enhancement (PE) |
| | Time-to- peak (TTP) |
| | Wash-in-slope (WIS) |
| | Washout rate (WOS) |
| | Curve shape index (CSI) |
| | Enhancement at first post-contrast image (EFP) |
| | Enhancement ratio (ER) |
| | Maximal variance in uptake (MVU) |
| | Variance in time to peak (VTTP) |
| | Variance in uptake rate (VUTP) |
| | Variance in washout rate speed (VWOS) |
| Textural [9], [35] | Contrast |
| | Correlation |
| | Energy |
| | Homogeneity |
| | Entropy |
| | Variance |
| | Sum average |
| | Sum variance |
| | Sum entropy |
| | Difference in variance (DV) |
| | Difference in entropy (DE) |
| | Information measure of correlation1 (IMC1) |
| | Information measure of correlation2 (IMC2) |
| | Maximal correlation coefficient (MCC) |
| Morphologic [34] | Size |
| | Circularity |
| | Irregularity |
| | Margin sharpness (mean gradient at margin) |
| | Variance in margin sharpness (VMS) |
| | Variance in radial gradient histogram (VRGH) |

## 5. CONCLUSION

We propose a feature extraction method for characterizing PK intra tumor heterogeneity in breast DCE-MRI using spatiotemporal wavelet kinetic features. The proposed Het Wave features aim to capture tumor heterogeneity by first partitioning the tumor into locally heterogeneous sub regions, and then characterizing spatiotemporal patterns of the contrast agent uptake and its spatial frequency information using wavelet coefficients. Pharmacokinetic-based heterogeneity partitioning was evaluated for extracting the Het Wave features. A wrapper-based feature selection method using genetic algorithm, and a logistic regression classifier with LOO cross validation were used to evaluate the prognostic value of the proposed features in classifying breast cancer recurrence risk as determined by a widely validated gene expression assay. Het Wave features provide superior ROC AUC when compared to a wide range of currently established, standard breast DCE-MRI features. The combination of Het Wave and standard features can give further classification improvement. This suggests that Het Wave could be a powerful feature extraction approach for characterizing tumor heterogeneity, providing valuable prognostic information.

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