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Shear wave elastography (SWE) examination using ultrasound elastography (USE) is a popular imaging procedure for obtaining elasticity information of breast lesions. Elasticity parameters obtained through SWE can be used as biomarkers that can distinguish malignant breast lesions from benign ones. Furthermore, the elasticity parameters extracted from SWE can speed up the diagnosis and possibly reduce human errors. In this paper, Shearlet transform and local binary pattern histograms (LBPH) are proposed as an original algorithm to differentiate malignant and benign breast lesions. First, Shearlet transform is applied on the SWE images to acquire low frequency, horizontal and vertical cone coefficients. Next, LBPH features are extracted from the Shearlet transform coefficients and subjected to dimensionality reduction using locality sensitivity discriminating analysis (LSDA). The reduced LSDA components are ranked and then fed to several classifiers for the automated classification of breast lesions. A probabilistic neural network classifier trained only with seven top ranked features performed best, and achieved 98.08% accuracy, 98.63% sensitivity, and 97.59% specificity in distinguishing malignant from benign breast lesions.
lesions. The high sensitivity and specificity of our system indicates that it can be employed as a primary screening tool for faster diagnosis of breast malignancies, thereby possibly reducing the mortality rate due to breast cancer.

**Keywords:** breast lesions; benign; malignant; shear wave elastography; shearlet transform; local binary pattern.

**INTRODUCTION**

Shear wave elastography (SWE) is a highly reproducible method which provides quantitative information of mechanical properties of tissue by imaging the shear wave propagation within the tissues and through the tissue surface [1, 2, 3, 4, 5, 6, 7]. In SWE, shear waves are induced in transverse directions. Then, the lateral spreading and the speed of propagation of these shear waves inside the tissues is recorded [8]. Elastography images are acquired by means of ultrafast ultrasonography, and the reconstructed images represent the speed at which the shear wave travels the tissue laterally [7, 9]. In the diagnosis of the breast, elastography is helpful in assessing the lesion stiffness by mapping the strain in the lesion and neighbouring tissues. The properties of breast lesions are evaluated within a region of interest (ROI) drawn manually by an electronic cursor directly on elastography images [10].

Breast lesions are typically categorized as malignant or benign based on their traits and the extent of risk [11]. The main features of breast lesions in ultrasound images consist of the distinctiveness and outline of the lesion margins, orientation, shape, boundary echoes, echo texture and echogenicity [12, 13, 14, 15]. Benign breast lesions look circular and oval with extreme boundary and homogenous internal echoes [14, 16, 17]. On the contrary, malignant breast lesions have unclear and indistinctive outline, may reveal heterogeneous echo patterns [14]. According to the breast imaging reporting and data system (BI-RADS) criteria (see Table 2), the assessment of location of the lesion, its’ the lesion characteristics and surrounding tissue are essential for the characterization of malignancies [18]. However, these characteristic measurements lack quantifiable information on the tissue elastic properties that could contribute to better a more accurate identification of cancer tissue which is harder, more rigid, and less compressible than normal breast tissue.
As a matter of fact, recent investigations underscore that elasticity measurements are useful for the diagnosis of malignant breast masses [6, 21, 22, 23]. In addition, other studies have shown that, besides the qualitative parameters (stiffness of the lesion and the adjacent tissues, shape and size of the lesion), the elasticity information derived through the SWE method can be used as significant markers to draw a distinction between benign and malignant lesions [24, 25]. In [26], maximum, minimum, and mean elasticity cut-off values namely: 37.1 kPa, 45.7 kPa, and 54.3 kPa have been respectively defined, to distinguish malignant and benign lesions through SWE technique. However, in other studies [27, 28, 29] the values that have been found significantly different are respectively: 80kPa [30], 30kPa [31] and 65kPa [27]. Many other studies reported that elasticity parameters derived from SWE differ in cancer and malignant tissues. Yet, there is a huge inter-study discrepancy that hampers clinical implementation of SWE technique for breast lesion classification [5, 27, 28, 32, 33, 34, 35, 36] (Please see Table 1).

Moreover, the assessment of breast lesions using SWE either with or without the ultrasound imaging has shown improvement when compared to conventional ultrasound imaging alone in identifying malignant lesions [3, 5, 23, 27, 31, 34, 35, 37, 38]. Many studies have also shown various other benefits of using SWE for breast lesion assessment. For instance, small (≤ 2cm) lesions [43, 44] as well as lesions in dense and stiff tissues can possibly be detected [42].
Table 1: Studies conducted using SWE image parameters for the identification of the two classes (benign and malignant).

<table>
<thead>
<tr>
<th>Author (year)</th>
<th>Modality</th>
<th>Breast lesions</th>
<th>Parameters/Features</th>
<th>Outcome of SWE alone</th>
</tr>
</thead>
<tbody>
<tr>
<td>Evans et al., 2010</td>
<td>US + SWE</td>
<td>Benign: 23, Malignant: 30</td>
<td>Mean elasticity</td>
<td>Acc = 91%, Sen = 97%, Spe = 83%</td>
</tr>
<tr>
<td>Chang et al., 2011</td>
<td>US + SWE</td>
<td>Benign: 93, Malignant: 89</td>
<td>Mean elasticity</td>
<td>Acc = 86.8%, Sen = 88.8%, Spe = 84.9%</td>
</tr>
<tr>
<td>Evans et al., 2012</td>
<td>US + SWE</td>
<td>Benign: 64, Malignant: 111</td>
<td>Mean and maximum elasticity</td>
<td>Acc = 89%, Sen = 95%, Spe = 77%</td>
</tr>
<tr>
<td>Chang et al., 2013</td>
<td>US + SWE + Strain elastography</td>
<td>Benign: 79, Malignant: 71</td>
<td>Mean and standard deviation of elasticity</td>
<td>Sen = 95.8%, Spe = 84.8%</td>
</tr>
<tr>
<td>Gweon et al., 2013</td>
<td>US + SWE</td>
<td>Benign: 269, Malignant: 120</td>
<td>Minimum, mean, maximum and ratio of elasticity</td>
<td>Sen = 88%, Spe = 90.6%</td>
</tr>
<tr>
<td>Lee et al., 2013b</td>
<td>US + 2D SWE + 3D SWE</td>
<td>Benign: 77, Malignant: 67</td>
<td>Mean, maximum and ratio of elasticity</td>
<td>Specificity improved by adding 2D and 3D SWE to US</td>
</tr>
<tr>
<td>Youk et al., 2014</td>
<td>US + SWE</td>
<td>Benign: 81, Malignant: 49</td>
<td>Mean, maximum, standard deviation of elasticity</td>
<td>Spe = 95.1%</td>
</tr>
<tr>
<td>Youk et al., 2013</td>
<td>US + Strain elastography + SWE</td>
<td>Benign: 269, Malignant = 120</td>
<td>All elasticity parameters</td>
<td>Reported downgrade of BI-RADS category 4a masses</td>
</tr>
<tr>
<td>Olgun et al., 2014</td>
<td>US + SWE</td>
<td>Benign: 83, Malignant: 32</td>
<td>Minimum, mean, maximum, ratio of elasticity</td>
<td>Sen = 97%, Spe = 95%</td>
</tr>
<tr>
<td>Au et al., 2014</td>
<td>US + SWE</td>
<td>Benign: 79, Malignant: 44</td>
<td>Mean, maximum, ratio of elasticity</td>
<td>Acc = 90.24%, Spe = 87.34%</td>
</tr>
<tr>
<td>Author (year)</td>
<td>Modality</td>
<td>Breast lesions</td>
<td>Parameters/Features</td>
<td>Classification</td>
</tr>
<tr>
<td>-----------------------</td>
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<td>-------------------------------------------------------------------------------------</td>
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</tr>
<tr>
<td>Kim et al., 2015 [44]</td>
<td>US + SWE</td>
<td>Benign: 155</td>
<td>Mean, maximum, ratio of elasticity</td>
<td>Sen = 68.2%, Spe = 87.1%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Malignant: 22</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lee et al., 2015 [69]</td>
<td>US + SWE + MRI</td>
<td>Benign +</td>
<td>Maximum of elasticity</td>
<td>Acc = 83.1%, Sen = 83.6%, Spe = 80%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Malignant: 71</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lee et al., 2015 [40]</td>
<td>US + SWE</td>
<td>Benign: 110</td>
<td>All SWE parameters</td>
<td>Sen = 86.7%, Spe = 97.3%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Malignant: 30</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Xian-Quan et al., 2015 [71]</td>
<td>US + SWE</td>
<td>Benign +</td>
<td>Minimum, mean, maximum, standard deviation and ratio of elasticity</td>
<td>Sen = 87%, Spe = 97%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Malignant = 302</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ng et al., 2016 [41]</td>
<td>US + SWE</td>
<td>Benign: 85</td>
<td>Minimum, mean, maximum, standard deviation and ratio of elasticity</td>
<td>Sen = 100%, Spe = 97.6%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Malignant: 74</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Choi et al., 2016 [70]</td>
<td>US + SWE</td>
<td>Benign: 7</td>
<td>Mean, maximum, and maximum stiffness color</td>
<td>Acc = 84.5%, Sen = 78.4%, Spe = 95.2%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Malignant: 74</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Li et al., 2015 [23]</td>
<td>US + SWE</td>
<td>Benign: 212</td>
<td>Velocity of shear wave</td>
<td>Sen = 67.9%, Spe = 86.3%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Malignant: 84</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Using computer-aided techniques**

<table>
<thead>
<tr>
<th>Author (year)</th>
<th>Modality</th>
<th>Breast lesions</th>
<th>Parameters/Features</th>
<th>Classification</th>
<th>Outcome of SWE alone</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lo et al., 2015 [46]</td>
<td>US + SWE</td>
<td>Benign: 57</td>
<td>First order statistics</td>
<td>Logistic regression</td>
<td>Acc = 81%, Sen = 61%, Spe = 91%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Malignant: 31</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Zhang et al., 2015b [48]</td>
<td>US + SWE</td>
<td>Benign +</td>
<td>Contourlet-based texture features</td>
<td>ROC and Fisher</td>
<td>Acc = 92.5%, Sen = 89.1%, Spe = 94.3%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Malignant: 161</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Zhang et al., 2016 [49]</td>
<td>US + SWE</td>
<td>Benign: 135</td>
<td>Deep learning features using DL architecture with RBMs and PGBM</td>
<td>SVM</td>
<td>Acc = 93.4%, Sen = 88.6%, Spe = 97.1%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Malignant: 92</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Acharya et al., 2017 [47]</td>
<td>US + SWE</td>
<td>Benign: 83</td>
<td>RLS and Hu’s moments are extracted from DWT coefficients + sBCRI</td>
<td>DT, LDA, QDA, SVM, PNN and KNN</td>
<td>Acc = 93.59%, Sen = 90.41%, Spe = 96.39%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Malignant: 73</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Although many quantitative parameters of lesion elasticity have been proposed, the mean elasticity has so far been reported as the best parameter in discriminating the breast lesions (malignant or benign) [5].

In general, the SWE method is not consider operator-dependent. However, a certain degree of variability may happen during the SWE image acquisition if too much force is exerted to the probe [45]. Hence, the reliability of the SWE imaging is dependent on the experience and training of the operator. Certain technical errors such as probe movement or compression can lead to unreliable results [1, 4, 32]. In addition, manual evaluation of elasticity parameters from SWE is laborious and susceptible to variabilities [45]. Thus, to overcome these technical and manual difficulties, several computer-aided diagnostic approaches have been proposed for autonomous classification of the two classes (malignant and benign). Amongst the state-of-the-art there are first order statistics [46], second order statistics [47], discrete wavelet transform (DWT) [47], contourlet transform [48] and deep learning [49] methods, that have shown improved diagnostic performance (specificity, sensitivity, and accuracy) in the distinction of breast lesions (benign or malignant) (Table 1). Thus, the employment of more advanced or novel techniques can potentially result in higher accuracy of breast lesions characterization, and thus improving patient outcomes.

In this paper, a new approach employing Shearlet transform and local binary pattern histograms (LBPH) to analyse SWE images towards improved categorization of breast lesions is proposed. The workflow of our method is shown in Figure 1. The SWE images are subjected to Shearlet transform to obtain three layers of frequency coefficients (low frequency, horizontal and vertical cones). LBPH is applied to these coefficients as a feature extraction step. This process is followed by the feature reduction using locality sensitive discriminating analysis (LSDA). The output is a reduced set of LSDA coefficients that are ranked using t-test. Finally, they are fed to the various classifiers with the goal to automatically differentiate if the breast lesion is benign or malignant.

![Figure 1: Block diagram of the proposed method.](image)

<table>
<thead>
<tr>
<th>Image</th>
<th>Preprocessing</th>
<th>Shearlet transform</th>
<th>Local binary pattern histogram</th>
<th>Feature reduction using LSDA</th>
<th>t-test</th>
<th>Classification</th>
</tr>
</thead>
</table>

Benign or Malignant

Table 2: BI-RADS mammographic assessment categories [53].
### METHODOLOGY

#### Image Acquisition

The SWE images necessary for this work were collected at the Department of Biomedical Imaging, University of Malaya Medical Centre, Malaysia, after the approval from institutional medical ethics committee board. In this study, 156 female Asian patients having either palpable lumps or lesions (83 benign and 73 malignant) of BI-RADS 4 and above, underwent a sonography examination. The patients were informed about the goal and risk of the study and they signed informed consent. Recruited patients underwent scanning using the Aixplorer ultrasound system (SuperSonic Imagine, Aixen Provence, France) with 15-4MHz linear transducer probe. Using SWE method, elastography images were obtained from the ultrasound B-mode grayscale images [41].

#### Pre-Processing

The images were trimmed (approximately 195 X 195 resolution) to retain only the SWE 3 X 3 cm colour map in the transverse plane. Then the coloured SWE images are changed to grayscale SWE images using adaptive histogram equalization [51].
Shearlet Transform

Shearlets belong to a category of directional multidimensional representation of systems and have profound impact on the encoding of multidimensional signals and images [52]. A shearlet is created by the dilation, shearing and translation of a function $\psi \in L^2(\mathbb{R}^2)$ known as the mother shearlet [52, 53, 54]. In this method, the frequency domain is divided into low-frequency part and two conic regions (horizontal and vertical cones). This idea is called as cone-adapted shearlets and was first proposed in [52]. Figure 3 shows the frequency tiling of the cone-adapted shearlet system generated by the classical shearlet. This technique can be seamlessly applied to images – see Figure 4a and 4b that show the horizontal and vertical cones obtained for both classes (benign and malignant).
Figure 3: Frequency plane and support.
(a) The tiling of frequency by the shearlets (b) The size of the frequency support of a shearlet (trapezoid of approximate size $2^j \times 2^j$)
Figure 4a: 3-layer shearlet coefficients of horizontal and vertical cones obtained for benign SWE image where the columns are organized in first, second, and third order (from left to right) and the rows are organized by first, second, and third order (from top to bottom) respectively.
Figure 4b: 3-layer shearlet coefficients of horizontal and vertical cones obtained for malignant SWE image where the columns are organized in first, second, and third order (from left to right) and the rows are organized by first, second, and third order (from top to bottom) respectively.
From these frequency coefficients (horizontal and vertical cones), we propose to extract LBPH features that are then evaluated for the two classes.

**Local Binary Pattern Histogram (LBPH)**

LBPH is a straightforward, resilient, and efficient texture descriptor [55, 56]. The LBPH is both grayscale and rotation invariant image texture. The LBPH feature vector for grayscale invariant measure is given by Equation 1:

$$LBP_{P,R}(x) = \begin{cases} 
\sum_{P=0}^{P-1} s(g_p - g_c) & \text{if } U(x) \leq 2 \\
P + 1 & \text{otherwise}
\end{cases}$$

where, $s(x) = \begin{cases} 1, & x \geq 0 \\
0, & x < 0
\end{cases}$

(1)

where $P$ is the number of points on the circumference of a circular neighbourhood of the radius $R$. The $g_c$ is the intensity of the centre pixel and the $g_p$, $p=0,1,\ldots,P-1$, the intensity of the $P$ points. In this paper, uniform LBPH for $P = 8, 16$ and $24$ and $R = 1, 2$ and $3$ respectively are evaluated from shearlet coefficients (horizontal and vertical cones). The uniform LBPH is calculated for different rotation at an angle of $a = \frac{2\pi}{P}$, where $P$ is the neighbourhood.

The uniform LBPH is denoted as $U_p(n, r)$, where $n$ is the number of 1’s gray levels in the LBPH pattern and $r$ corresponds to the rotation of the pattern. From the LBPH calculated at each angle $a$, neighbourhood $P$, and radius $R$, histograms are obtained denoted as $h_n(U_p(n, r + a))$.

**Feature Reduction and Ranking**

In this paper, LBPH features are computed from shearlet transformed SWE images. A total of 9424 LBPH features are obtained from the coefficients of horizontal and vertical cones of SWE images. Locality sensitive discriminant analysis (LSDA) technique is applied to the extracted features for dimensionality reduction (30 LSDA coefficients).
In this section, a concise explanation of LSDA algorithm is given [57]. Consider $n$ data samples $x_1, x_2, \ldots, x_n \in R^n$ sampled from the underlying submanifold $M$. Further, a nearest-neighbour graph $G$ can be formulated to represent the structure of $M$. For every data points $x_i$, its k-nearest neighbours are computed and the border between $x_i$ and its neighbours is defined.

In LSDA, the between-class separability is described as

$$\max \sum_{i,j} (y_i - y_j)^2 W_{b ij}$$

(2)

The within-class compactness is described as

$$\min \sum_{i,j} (y_i - y_j)^2 W_{w ij}$$

(3)

Where $y_i$ is the one-dimensional illustration of $x_i$. A reasonable basis for choosing a good map is to optimize the two functions ($G_b$ and $G_w$). $W_{b ij}$ and $W_{w ij}$ are weight matrices.

It is very difficult to select the best features which can be used as distinct features to classify the benign and malignant breast lesions. In order to identify the useful and highly significant features, t-test ranking approach is used to obtain the ranks for each significant feature [58]. Subsequently, highly-ranked features are fed into the classifier for the identification of two classes and are used further in the classification process. The t-test identifies the significance of features by calculating the mean. This test returns the p-value and t-value. The feature is ranked accordingly with the t-value in descending order.

**Classification**
Features that are ranked as best are fed to six classifiers: decision tree (DT) [59], linear discriminant analysis (LDA) [60], quadratic discriminant analysis (QDA) [60], support vector machine (SVM) with polynomial kernel of order 1, 2, 3 and radial kernel function (RBF) [61], probabilistic neural network (PNN) [62] and k-nearest neighbour (KNN) [63] and these classifiers are evaluated using the ten-fold cross-validation approach.

RESULTS

A total of 156 SWE images (83 benign and 73 malignant) are subjected to Shearlet transform to obtain different frequency coefficients (low frequency, horizontal and vertical cones). From these coefficients, a total of 9424 LBPH features are calculated and LSDA is performed on these features to reduce the dimensionality. The normalized mean and standard deviation (SD) values of 30 LSDA coefficients obtained from the malignant and benign lesions are illustrated in Table 3. Figure 5 shows the bar chart of seven highly ranked features that are fed into the classifiers.

<table>
<thead>
<tr>
<th>LSDA Coefficients</th>
<th>Benign mean</th>
<th>Benign SD</th>
<th>Malignant Mean</th>
<th>Malignant SD</th>
<th>t-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>L6</td>
<td>0.466</td>
<td>0.100</td>
<td>0.380</td>
<td>0.0987</td>
<td>5.3861</td>
</tr>
<tr>
<td>L9</td>
<td>0.813</td>
<td>0.143</td>
<td>0.705</td>
<td>0.175</td>
<td>4.1683</td>
</tr>
<tr>
<td>L7</td>
<td>0.435</td>
<td>0.081</td>
<td>0.389</td>
<td>0.0668</td>
<td>3.8517</td>
</tr>
<tr>
<td>L12</td>
<td>0.423</td>
<td>0.187</td>
<td>0.323</td>
<td>0.160</td>
<td>3.6369</td>
</tr>
<tr>
<td>L3</td>
<td>0.144</td>
<td>0.0341</td>
<td>0.195</td>
<td>0.142</td>
<td>2.9536</td>
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<tr>
<td>L5</td>
<td>0.586</td>
<td>0.114</td>
<td>0.628</td>
<td>0.0713</td>
<td>2.8204</td>
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<tr>
<td>L10</td>
<td>0.348</td>
<td>0.0722</td>
<td>0.391</td>
<td>0.141</td>
<td>2.3632</td>
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<tr>
<td>L4</td>
<td>0.810</td>
<td>0.128</td>
<td>0.843</td>
<td>0.0397</td>
<td>2.2397</td>
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<td>L15</td>
<td>0.328</td>
<td>0.130</td>
<td>0.275</td>
<td>0.235</td>
<td>1.7145</td>
</tr>
<tr>
<td>L13</td>
<td>0.434</td>
<td>0.163</td>
<td>0.474</td>
<td>0.203</td>
<td>1.3442</td>
</tr>
<tr>
<td>L2</td>
<td>0.968</td>
<td>0.108</td>
<td>0.983</td>
<td>0.005</td>
<td>1.3155</td>
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<tr>
<td>L14</td>
<td>0.402</td>
<td>0.198</td>
<td>0.367</td>
<td>0.180</td>
<td>1.1744</td>
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<tr>
<td>L16</td>
<td>0.261</td>
<td>0.163</td>
<td>0.234</td>
<td>0.154</td>
<td>1.0594</td>
</tr>
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<td>L1</td>
<td>0.870</td>
<td>0.098</td>
<td>0.881</td>
<td>0.004</td>
<td>1.0148</td>
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<tr>
<td>L8</td>
<td>0.873</td>
<td>0.117</td>
<td>0.881</td>
<td>0.056</td>
<td>0.5663</td>
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<td>L29</td>
<td>0.499</td>
<td>0.038</td>
<td>0.505</td>
<td>0.108</td>
<td>0.4617</td>
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<td>L20</td>
<td>0.652</td>
<td>0.194</td>
<td>0.664</td>
<td>0.133</td>
<td>0.4531</td>
</tr>
<tr>
<td>L18</td>
<td>0.457</td>
<td>0.045</td>
<td>0.465</td>
<td>0.156</td>
<td>0.4360</td>
</tr>
<tr>
<td>L23</td>
<td>0.355</td>
<td>0.167</td>
<td>0.347</td>
<td>0.096</td>
<td>0.3544</td>
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<tr>
<td>L17</td>
<td>0.391</td>
<td>0.086</td>
<td>0.382</td>
<td>0.202</td>
<td>0.3410</td>
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<tr>
<td>L19</td>
<td>0.485</td>
<td>0.081</td>
<td>0.479</td>
<td>0.167</td>
<td>0.3140</td>
</tr>
<tr>
<td>L26</td>
<td>0.352</td>
<td>0.153</td>
<td>0.347</td>
<td>0.067</td>
<td>0.2943</td>
</tr>
<tr>
<td>L22</td>
<td>0.461</td>
<td>0.113</td>
<td>0.457</td>
<td>0.068</td>
<td>0.2691</td>
</tr>
<tr>
<td>L28</td>
<td>0.478</td>
<td>0.177</td>
<td>0.484</td>
<td>0.082</td>
<td>0.2500</td>
</tr>
<tr>
<td>L30</td>
<td>0.517</td>
<td>0.043</td>
<td>0.513</td>
<td>0.121</td>
<td>0.2468</td>
</tr>
<tr>
<td>L11</td>
<td>0.189</td>
<td>0.106</td>
<td>0.192</td>
<td>0.102</td>
<td>0.1425</td>
</tr>
<tr>
<td>L25</td>
<td>0.552</td>
<td>0.135</td>
<td>0.550</td>
<td>0.040</td>
<td>0.1215</td>
</tr>
<tr>
<td>L27</td>
<td>0.559</td>
<td>0.167</td>
<td>0.557</td>
<td>0.104</td>
<td>0.1200</td>
</tr>
<tr>
<td>L24</td>
<td>0.531</td>
<td>0.142</td>
<td>0.533</td>
<td>0.149</td>
<td>0.0736</td>
</tr>
<tr>
<td>L21</td>
<td>0.440</td>
<td>0.052</td>
<td>0.440</td>
<td>0.111</td>
<td>0.0269</td>
</tr>
</tbody>
</table>

Figure 5: Bar chart of mean values of LSDA coefficients obtained from malignant and benign breast lesions of SWE images.

It can be seen from Table 3 and Figure 5 that a clear differentiation can be observed in the feature values of the two classes. Few feature values have higher
values for malignant lesions than benign because the occurrence of sudden variations in the image pixels present in malignant lesions is more than benign lesions. In other words, the malignant tissues become harder (or stiffer) as compared to a benign stage, thus, exhibiting sharp local changes in the SWE images. In benign lesions, the tissues are softer so the changes occurring in the pixels are less abrupt as compared to malignant, therefore, exhibit fewer high amplitude SWE image values.

Best ranked coefficients are used to train and validate the six classifiers that we chose. Table 4 summarizes classification results Figure 6 shows the plot of accuracy (%) achieved using various numbers of features with PNN classifier.

Table 4: Classification results obtained using different classifiers.

<table>
<thead>
<tr>
<th>Classifiers</th>
<th>No of Features</th>
<th>tp</th>
<th>tn</th>
<th>fp</th>
<th>fn</th>
<th>acc</th>
<th>sen</th>
<th>spe</th>
</tr>
</thead>
<tbody>
<tr>
<td>DT</td>
<td>8</td>
<td>71</td>
<td>79</td>
<td>4</td>
<td>2</td>
<td>96.15%</td>
<td>97.26%</td>
<td>95.18%</td>
</tr>
<tr>
<td>LDA</td>
<td>8</td>
<td>72</td>
<td>81</td>
<td>2</td>
<td>1</td>
<td>98.08%</td>
<td>98.63%</td>
<td>97.59%</td>
</tr>
<tr>
<td>QDA</td>
<td>4</td>
<td>59</td>
<td>73</td>
<td>10</td>
<td>14</td>
<td>84.62%</td>
<td>80.82%</td>
<td>87.95%</td>
</tr>
<tr>
<td>KNN</td>
<td>5</td>
<td>69</td>
<td>76</td>
<td>7</td>
<td>4</td>
<td>92.95%</td>
<td>94.52%</td>
<td>91.57%</td>
</tr>
<tr>
<td>PNN</td>
<td>0.02</td>
<td>72</td>
<td>81</td>
<td>2</td>
<td>1</td>
<td>98.08%</td>
<td>98.63%</td>
<td>97.59%</td>
</tr>
<tr>
<td>SVM RBF</td>
<td>2.1</td>
<td>72</td>
<td>81</td>
<td>1</td>
<td>1</td>
<td>98.08%</td>
<td>98.63%</td>
<td>97.59%</td>
</tr>
<tr>
<td>SVM Poly 1</td>
<td>8</td>
<td>71</td>
<td>81</td>
<td>2</td>
<td>2</td>
<td>97.44%</td>
<td>97.26%</td>
<td>97.59%</td>
</tr>
<tr>
<td>SVM Poly 2</td>
<td>8</td>
<td>72</td>
<td>80</td>
<td>3</td>
<td>1</td>
<td>97.44%</td>
<td>98.63%</td>
<td>96.39%</td>
</tr>
<tr>
<td>SVM Poly 3</td>
<td>8</td>
<td>69</td>
<td>80</td>
<td>3</td>
<td>4</td>
<td>95.51%</td>
<td>94.52%</td>
<td>96.39%</td>
</tr>
</tbody>
</table>

where *tp* = true positive, *tn* = true negative, *fp* = false positive, *fn* = false negative
*acc* = accuracy, *sen* = sensitivity, and *spe* = specificity.
Figure 6: Plot of accuracies achieved using a different number of features with PNN classifier.

Table 4 reveals that the PNN classifier outperformed the rest of the classifiers in distinguishing the malignant lesions from benign ones with an accuracy of 98.08% and a sensitivity and specificity of 98.63%, and 97.59% respectively with just seven features.
DISCUSSION

In this study, a new algorithm is developed for texture analysis of SWE images. The goal is to assess the tissue elasticity to distinguish benign and malignant classes. Shearlet based image texture features are extracted using LBPH to assess the presence of malignancies in the breast lesions. Shearlet transform employs the power of multiscale with an exclusive property that captures the geometry of multidimensional data. This technique has been demonstrated efficient in illustrating images comprising edges [64].

Using other different methods such as first order statistics, second order statistics, DWT, contourlet transform, and deep learning, few researchers have extracted various texture features from SWE images to characterize the malignant and benign classes (Table 1).

Lo et al. [46], applied first order statistics method to evaluate various SWE image texture features to characterize the breast lesions. Using their proposed technique, an accuracy of 83% for the differentiation of BI-RADS 4 category of breast lesions has been reported. Recently, Zhang et al. [48] employed contourlet-based first order statistics for texture analysis of SWE images. Their study assessed the SWE texture features from the contourlet sub bands for analysing the elasticity information of breast lesions. An accuracy of 92.5% is reported by their technique in the diagnosis of the breast lesions. However, the first order statistical technique employed to extract various features are unable to capture the higher–order correlation present in SWE images [65]. Hence, in order to assess the fine variations of image pixels, second- [48] or higher-order feature extraction techniques [47, 49] are necessary [65].

Towards this goal, in 2016, Zhang et al. [49] employed a deep learning (DL) based technique on SWE images for classification of breast tumours. Their team built a DL model comprised of the point-wise gated Botlzmann machine (PGBM) and the restricted Botlzmann machine (RBM) for the classification. The study results exhibited 93.4% accuracy for the detection of benign and malignant breast tumours. Even though DL techniques are gaining popularity in image processing, it takes very long time and significant effort to build an image database to train them. The training is also computationally expensive.

In [47], DWT was coupled with second order features in the categorization of the two classes (benign and malignant). A new shear wave breast cancer risk index (sBCRI) was proposed in this study [47]. It is a single number (threshold) for the differentiation of malignant and benign lesions. Their experiential results showed
better accuracy of 93.59% using second order statistical features. However, wavelets are known to have restricted competency in handling with directional information to capture anisotropic features [67].

On the other hand, the shearlet transform offers the following advantages: (i) it permits the use of compactly supported analytical functions both in the frequency and space domain and (ii) has fast algorithmic implementation [67]. LBPH is one of the most powerful texture descriptors for representing local structures and is computationally inexpensive [68]. The joint properties of shearlet and LBPH methods make them as an excellent choice for analysis of SWE images to separate the two classes.

Thus, as compared to other published studies (Table 1), the main novelty of our method is the accuracy performance in the identification of breast lesions (malignant and benign classes). Our proposed technique achieved the highest accuracy, sensitivity, and specificity of 98.08%, 98.63%, and 97.59% respectively in categorizing the two classes (benign and malignant). In addition, compared to the five-fold cross-validation method [48], our proposed algorithm was validated using ten-fold cross-validation technique which is more robust. Thus, using the proposed technique the malignancies can be detected faster and accurately (due to high sensitivity); even the unnecessary biopsies can be avoided (due to high specificity). Such a system could be beneficial if used in hospitals or polyclinics to screen women for the risk of breast lesions. In our future studies, we will be exploring the possibility of identifying multiple malignant breast lesions in one patient using SWE images with our novel strategy.

**CONCLUSION**

Despite participating in frequent breast screening, many women with breast cancers failed to be diagnosed at an earlier phase and consequently, die. Therefore, an automated diagnostic method with an improved diagnostic performance is required for the early identification of malignancies. In this paper, Shearlet and LBPH combined algorithm is proposed to characterize the benign and malignant lesions. Our proposed methodology has attained the highest accuracy, sensitivity, and specificity of 98.08%, 98.63% and 97.59% in the characterization of malignancies using seven top performing features extracted from SWE images. The algorithm is fully automated and can be used in assessing the breast lesions accurately at an early stage and thereby providing time for further treatment. Our algorithm was developed using
a cohort of 156 Asian women. In future, we intend to validate our system with more subjects including Caucasians.

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