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Texture-Based Breast Cancer Nodule Classification in Ultrasound Imaging Using Adaptive Median Filtering and MLP

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ABSTRACT

The Ultrasonography (USG) is an imaging technique used to identify breast abnormalities. The benefits of ultrasound imaging encompass its non-invasive nature and absence of radiation exposure. Nonetheless, ultrasound imaging outcomes often involve issues that cause variations in physicians' interpretations of breast ultrasound images. Computer-Aided Diagnosis (CAD) is a computational approach that offers an objective secondary assessment in identifying the attributes of nodules in breast ultrasound images. The CAD method includes an image preparation phase that encompasses RoI selection, filtering, texture feature extraction, and classification. The filtering procedure is executed utilizing a median adaptive filter and a median filter. Texture feature extraction is performed with nine histogram features and 21 Gray Level Co-occurrence Matrix (GLCM) features. Extraction results from Scilab indicate that employing 30 texture features enables the Multi Layer Perceptron (MLP) to categorize cystic and solid mass nodules with an accuracy of 88.89%, while utilizing 10 texture features yields an accuracy of 80.56%.

1. INTRODUCTION

In 2022, the WHO reported that roughly 2.3 million women were diagnosed with breast cancer, leading to 670,000 fatalities globally[1]. This issue must be resolved promptly to avert fatal consequences. The detection accuracy of breast nodules has become crucial for enhancing women's life expectancy globally and reducing unnecessary invasive procedures. Breast ultrasound (US) is widely used as an imaging technique for cancer detection due to its real-time functionality, absence of radiation, and cost efficiency. Speckle noise, decreased contrast, and indistinct nodule margins significantly affect ultrasound images, thereby limiting radiologists' diagnosis and decision-making assessments [2][3][4].

To resolve this issue, Computer-Aided Diagnosis (CAD) has been developed to aid radiologists in the classification and identification of breast cancer. Several previous studies indicate the efficacy of CAD systems using texture analysis for the classification of ultrasound images. The Gray Level Co-occurrence Matrix (GLCM) feature is frequently used to detect breast cancer using texture analysis. This feature has been demonstrated to distinguish between benign and malignant breast nodules[5][6]. Simultaneously, first-order statistical histogram parameters, such as mean, variance, skewness, kurtosis, and entropy, are often used to characterize tissue anomalies and the overall gray level distribution [7][8].

The effectiveness of texture-based classification is primarily determined by the quality of preprocessing, especially in terms of speckle noise reduction, which significantly affects the stability and reliability of the processed texture features[3][9]. Adaptive filtering methods, such as adaptive median filtering, provide superior effectiveness compared to traditional static filters by significantly reducing speckle noise while maintaining critical structural and textural characteristics of breast tumors [3][10]. However, some recent studies have implemented speckle reduction as an independent preprocessing step but have not integrated it into a comprehensive system that combines texture feature extraction and classification.

Recent studies have employed traditional machine learning techniques, including Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Artificial Neural Networks (ANNs), in computer-aided diagnostic (CAD) systems for breast ultrasound[11][12][13][14]. Multilayer Perceptron (MLP) is still a good classifier among ANN-based methods because it can model nonlinear relationships between texture features. This capability is supported by previous research, which indicates that texture-based classification of thyroid nodule ultrasound images using an MLP classifier can achieve accuracy rates as high as 86.1%[15]. To facilitate such analysis, the WEKA machine learning platform provides an open-source, standardized, and reproducible framework for implementing and evaluating MLP classifiers [3].

Analysis of previous studies shows that most breast ultrasound computer-aided detection (CAD) techniques utilize MATLAB or Python frameworks for image processing and classification [3][11][12][13][14]. The application of many open-source systems, such as SCILAB for texture feature extraction and WEKA for machine learning classification, has been inadequately addressed in the literature. This gap indicates the potential to develop a lightweight, entirely open-source, and reproducible CAD system that effectively classifies breast nodules using minimal datasets.

This research proposes a method for categorizing breast cancer nodules by breast ultrasound imaging. This process applies adaptive median filtering to reduce speckle noise, integrates first-order statistic histogram data with second-order GLCM texture features derived from the SCILAB platform, and classifies with multilayer perceptron executed in WEKA Machine

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Learning. Therefore, this contribution research is developing a fully open-access, cross-platform CAD system that is efficient, user-friendly, and compatible with small datasets.

2. METHODS

2.1. Material

This study used a dataset taken from RSUD Tugurejo in Semarang, Indonesia, as illustrated in Figure 1. The dataset is an RGB image consisting of 36 ultrasound images, with nine solid nodules and 27 cystic nodules.

Figure 1. The example of Ultrasound Image

This study comprises three primary stages: pre-processing, feature extraction, and classification, as shown in Figure 2. After selecting the Region of Interest (RoI) by identifying nodules in the ultrasound images, the following stages of nodule pre-processing and feature extraction are executed with SCILAB. Meanwhile, the classification process was executed using the mathematical outcomes from SCILAB and then processed on the machine learning platform WEKA.

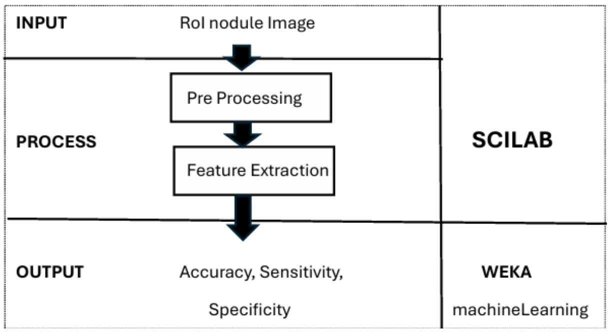

Figure 2. Block diagram

2.2. Method

2.2.1 Pre-Processing

The breast ultrasound images contain noise and marking. The Region of Interest (RoI) identified to locate the nodule in the image. After converting the nodule images, then the RoI RGB Image was converted to grayscale images, followed by filtering process. The filtering process was performed to remove speckle noise and picture marks, which improved the image quality. The filtering methods applied are median filtering and adaptive median filtering.

The median filter operates based on statistical value. This filter performs by replacing the original pixel intensity value with the median value of the surrounding pixels. Median filters preserve edge sharpness and images with reduce blurriness. The second filter is the adaptive median filter, which is a modification of the regular median filter. The adaptive median filter operates with a variable window size that adjusts according to the local properties of the image. This filter categorizes a pixel as noisy or non-noisy by comparing it with its adjacent pixels. If the central pixel is identified as noisy, the window size is dynamically enlarged (up to a specified maximum size) until a clean (non-noisy) median value is found[3][16][17].

2.2.2 Feature Extraction and Selection

The statistical features of the first-order histograms used are mean, standard deviation, variance, entropy, kurtosis, skewness, energy, maximum intensity, and minimum intensity. Meanwhile, the GLCM texture features used are 21 in total [18][19]. The calculation of information gain begins with the calculation of entropy before feature splitting as show in eq. (1).

$$Info\ (D) = \sum_{i=1}^{c} p_i \log_2 p_i \tag{1}$$

Where c is the data classes, while p_i is the samples of data for class i. Then calculate the entropy after feature splitting.

$$Info_A\ (D) = \sum_{j=1}^{v} \frac{|D_j|}{|D|} \times Info\ (D_j) \tag{2}$$

With A being feature, v a possible value for attribute A, $|D|$the total number of the samples of data, and $|D_j|$ the samples of data for sample j, as shown in eq. (2). The information gain value can be calculated as shown in eq. (3) [20][21][22].

$$Gain\ (A) = |Info\ (D) - Info_A\ (D)| \tag{3}$$

2.2.3 Classification

This classification method combines a Multi-Layer Perceptron (MLP) with the Backpropagation Error (BEP) algorithm. The Multilayer Perceptron (MLP) is a classification method based on an artificial neural network containing many layers as depicted in Figure 3.

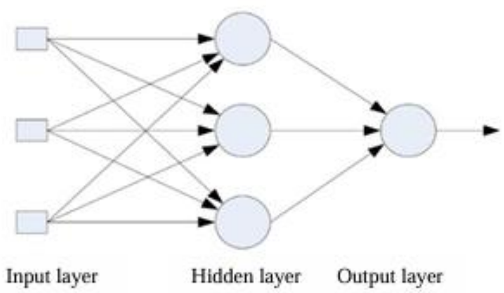

Figure 3. Example of Multi-Layer Perceptron[3]

2.3 Evaluation

The selection and classification features process involves the assistance of Machine Learning Weka. After that, The performance of the features was determined by using certain statistical indicators, including accuracy, sensitivity, and specificity using eq. (4)-(6)[3][20][21].

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \times 100\% \tag{4}$$

$$Sensitivity = \frac{TP}{TP + FN} \times 100\% \tag{5}$$

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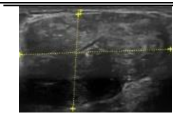
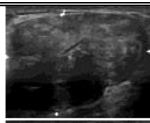
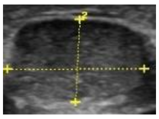
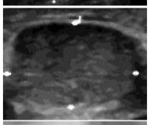
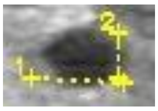
$$Specificity = \frac{TN}{TN + FP} \times 100\% \tag{6}$$

3. RESULTS AND DISCUSSION

3.1. Results

Filter process was conducted to reduce of speckle noises and label. As shown as Table 1, Neither filter is currently able to minimize the marking at each end successfully. The median adaptive filter only marginally reduces marking at each end of the marking. The marking is still faintly visible. The result of the median filter is that it still makes the marking very clearly visible, because the adaptive median filtering method works by setting the window size to its maximum value [3][23][24]. The maximum size can be specified at the beginning of the screening procedure. The maximum, minimum, and median values are determined for each window. Next, this filtering strategy assigns a new value to specific pixels, hence improving the filtering process.

Table 1. Results of each filter

Original Image	Median Filter	Adaptive Median Filter
		
		
		

The SI value in the measurement index indicates the remaining noise content in the image after filtering. The noise filtering process is good if it can reduce the SI value. In this experiment, the SI value for the filter of adaptive median was lower than the median filter as shown as Figure 4. This indicates that to reduce the noise of images, the adaptive median filter is more effective then another filter. Based on the results, the adaptive median filter is more effective at minimizing noise and picture artifacts in ultrasound images [24][25]. These results are comparable to the previouse research, that demonstrated that adaptive filters can efficiently reduce noise in ultrasound images while preserving image edges and maintaining image information values[3].

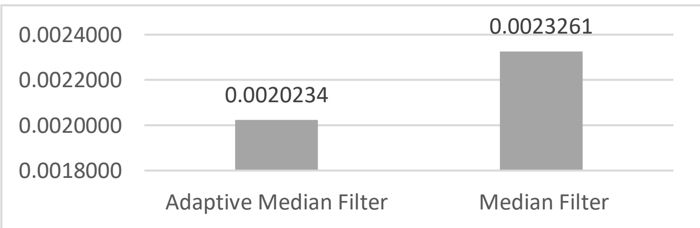


Figure 4. The Comparison speckle index

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After the pre-processing stage, the feature extraction method produced 30 features, consisting nine histogram features and 21 GLCM features. The MLP classifier in the WEKA machine learning platform was used to classify these features.

The selection features with information gain value, indicated that 10 texture features have significant impact on the categorization as shown in Table 2. Texture features with a Gain value bigger than zero are those that have a significant impact on the classification process. The more value variations there are, the higher the probability that a characteristic will have a high information gain value.

Table 2. The Results of feature selection

Texture Feature (Histogram & GLCM)	*Information Gain*
Kurtosis	0.34
Smothness	0.34
Varian	0.34
Std	0.34
Modus	0.339
Sentro	0.311
Entropi	0.311
Cprom	0.285
IDN	0.255
Dvar	0.237
Kontras	0
Energi	0
Skewness	0
ASM	0
SSVar	0
Correlation	0
SAV	0
IDM	0
Acorr	0
Cshade	0
Mprob	0
Idiff	0
Dissi	0
IMCorr2	0
INN	0
IMCorr1	0
Svar	0
Entropy	0
Dentro	0
Mean	0

The MLP classifier was implemented using the WEKA 3.8 platform. As presented in Table 3, the network architecture consisted of 10 hidden units (H=10). The training process was conducted over 500 epochs (N=500), employing a learning rate of 1.0 (L=1.0) and a momentum of 0.2 (M=0.2). These parameters were selected to balance the trade-off between training speed and the ability of the model to generalize across the ultrasound images based on the texture-features.

Table 3. The Parameter of MLP

ROC Area (AUC)	Learning Rate (L)	Epoch (N)	Hidden Layer (H)
0,815	1.0	500	10

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The classification performance using the Multilayer Perceptron (MLP) algorithm was evaluated with 10-fold cross-validation. The categorizes the model's performance as a 'good classification,' as it exceeds the 0.8 threshold, as shown in Table 3.

As depicted in Table 4, the classification result showed an accuracy of 88.89%, and the classification results for the selected data are 80.56%. Based on this data, it indicates that texture characteristics can detect nodules with cystic or solid masses.

Table 4. The Results of Classification

Evaluation	Before Feature Selection (30 features)	After Feature Selection (10 features)
Accuracy	88,89%	80,56%
Sensitivity	77,78%	60%
Specificity	92,59%	88,46%

In Table 3, applying 30 texture characteristics generated an accuracy, sensitivity, and specificity of 88.89%,77.78%, 92,59%. Whereas applying 10 texture features obtained an accuracy, sensitivity, and specificity of 80.56%, 60%, 88,46%. This suggests that the feature selection strategy utilizing information gain was not sufficiently effective in classifying breast cancer nodules in ultrasound images using texture features. The different feature selection methods can be utilized to improve classification results, such as Correlated-based Feature Selection (CFS) for the future research [26]. Furthermore, to acquire better classification results, different classifier, like SVM, KNN, ResNet 50 can be applied[26][27][28].

This research has successfully developed a CAD system by using Scilab software, spanning the complete process from RoI selection and image filtering to texture feature extraction from breast ultrasound images. This CAD system is capable of conducting histogram and GLCM extraction techniques with relatively quick computation times. Overall, the extraction results from this CAD are able to recognize the characteristics of solid and cystic nodules well. This is proven by the accuracy percentage results in the classification process [29]. The disadvantage of this work is that it has not yet been able to construct a GLRLM extraction technique with a low calculation time, thus future development and refinement of the algorithm are needed for better results[30][31].

4. CONCLUSION

Based on the analysis of the outcomes of nodule classification in breast ultrasound photos that has been completed, it can be concluded that improving the quality of ultrasound images can be done through the process of Region of Interest (RoI) and filtering using an adaptive median filter. Texture features in ultrasound image nodules can be obtained using the histogram and GLCM methods. The findings of 10-fold cross-validation with machine learning Weka reveal an accuracy of 88.89% using 30 texture features and 80.56% using 10 texture features. Therefore, the more texture features used, the more nodular information will be gathered, leading to improved accuracy in the categorization process.

Future studies could improve breast cancer malignancy diagnosis by including other malignancy factors, such as morphological characteristics. Furthermore, different feature extraction and selection methods could be implemented to enhance classification outcomes.

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This research is limited with small primary dataset from Tugu Hospital. Consequently, there is a potential risk of overfitting and less reliable outcomes. To address these limitations, future research should evaluate this learning model using another larger dataset (primer or secondary dataset) to improve the capability and ensure more robust performance across different clinical scenarios.

5. ACKNOWLEDGMENT

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6. AUTHORS' NOTE

The authors declare that there is no conflict of interest regarding the publication of this article. The authors confirmed that the paper was free of plagiarism.

7. AUTHORS' CONTRIBUTION/ROLE

Eli Ermawati: Conceptualization, Methodology, Writing Original Draft; Hesti Khuzaimah Nurul Yusufiyah: Format Analysis, data Curation, Supervision; Edi Daenuri Anwar: Formal Analysis, review, and Editing; Muhammad Ardhi Khalif: Formal Analysis, Review, and Editing, Investigation; Ida Nurcahyani: Formal Analysis, Review, Proofreading.

8. AI USE AND DECLARATION OF GENERATIVE AI USE

During the preparation of this work, the authors used Grammarly in order to improve the readability and language of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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