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Research Article

Enhancing Breast Cancer Detection: A Hybrid Approach Integrating Local Binary Pattern Features and Deep Learning Insights from Mammogram Images

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Abstract:

Early identification of breast cancer improves treatment outcomes and lowers mortality rates. Mammogram images are useful for diagnosis, but their interpretation can be difficult and time-consuming. The current study analyzes the feasibility of promoting handmade and deep learning features to enhance the accuracy of breast cancer identification using mammography pictures. Previously, manual feature extraction has been labor-intensive and inconsistent. Furthermore, deep learning systems frequently suffer from limited data and architectural inefficiencies. To overcome these problems, we provide a novel strategy that makes use of both local binary pattern (LBP) features and automatic feature extraction from seven deep learning models. The concatenated LBP97.5%, and SVM and KNN classifiers trained on the hybrid feature beat existing state-of-the-art models. Our findings indicate the usefulness of this hybrid feature technique. This work demonstrates the potential of the suggested feature extraction strategy in improving classifier performance for breast cancer identification from mammography images. Our technique shows promise for early and more accurate diagnosis, contributing to better patient outcomes in the fight against breast cancer.

1. Introduction

Breast cancer remains an important health issue worldwide, seeking early detection to improve treatment efficacy and minimize fatality rates. Mammogram images are widely utilized to diagnose breast cancer, providing important information about possible malignancies.

However, the extensive determination of these images provides difficulties, typically necessitating significant time and skill. This research explores into a ground-breaking exploration: the combination of handcrafted and deep learning features aimed at strengthening the precision of breast cancer identification from mammography images. This paper's technique ingeniously combines standard feature engineering with advanced deep learning techniques, with a view of reinventing breast cancer detection from mammogram images. This novel strategy aims to capitalize on the strengths of both methodologies while addressing their particular shortcomings. Local Binary Pattern (LBP) features are a key component of the technique. LBP, an established texture analysis technology, captures detailed local patterns in photos. By quantifying variations in pixel intensities, LBP improves the ability to recognize subtle textures and anomalies that may indicate the existence of carcinoma of the breast. The approach is further strengthened by deep learning, which is well-known for its ability to extract features automatically. Seven specific deep learning models, each intended to derive particular insights from the data, integrate themselves to deliver a complete awareness of the mammography images. This ensemble approach leverages into the images' complex hierarchical properties, allowing for more sophisticated detection. The merging of LBP characteristics with deep learning-derived features is key to the process. This hybrid feature set is created by smoothly merging structured LBP features with abstract features generated from deep

learning models. This combination ensures a comprehensive representation of the mammography pictures, utilizing both granular textural nuances and high-level learning aspects.
The concatenated hybrid feature set serves as the basis for training Support Vector Machines (SVM) and K-Nearest Neighbor (KNN) classifiers. These classifiers, noted for their success in medical image analysis, include an enhanced feature space that includes both LBP-derived textures and deep learning-illuminated features.
This combination enables the classifiers to make informed and precise decisions about probable breast cancer indicators. The methodology is thoroughly evaluated and compared to existing state-of-the art models. Accuracy, sensitivity, specificity, and other indicators are included in a full performance review. The study's comparison of this approach to known methodologies demonstrates the hybrid methodology's better effectiveness and potential. In practice, the methodology is tested and validated on a wide group of mammography pictures. The study's technique intends to transform the landscape of breast cancer diagnosis by strategically integrating LBP and deep learning, resulting in earlier diagnoses, better treatment outcomes, and increased patient well-being.

2. Literature Review

Breast cancer is an important worldwide health issue, and early detection remains critical in improving treatment outcomes and minimizing mortality rates. Over the years, researchers have tried with many strategies and methodologies to improve the accuracy of breast cancer detection using mammography images. This literature review provides an overview of major studies that contributed establish a hybrid approach that incorporates LBP features and deep learning insights. The table 1 provides a concise overview of recent studies in breast cancer detection, highlighting the methodology, datasets used, achieved accuracy, and associated limitations.
The "VGG-19 + LBP" technique efficiently overcomes several limitations in breast cancer diagnosis. By exploiting VGG-19's transfer learning capabilities, the model obtains the capacity to recognize several cancer subtypes and generalize from limited datasets. The implementation of the Local Binary Pattern (LBP) improves the model's ability to identify minuscule texture patterns, addressing challenges such as limited annotations and synthetic data diversity.
This fusion establishes a balance between accuracy and interpretability, which reduces ensemble complexity. Furthermore, the combined features enable navigate image quality deviations and disparate class distributions, making the technique appropriate for a wide range of datasets. Overall, the "VGG-19 + LBP" strategy offers a strong answer for improving breast cancer detection outcomes.

3. Materials and Methodology

This section provides the methodology and materials to examine mammograms for early

Table.1 *Literature Review*

Ref	Methodology	Dataset	Accuracy (%)	Limitation
[1]	Deep learning with transfer learning	TCGA Breast Cancer Dataset	87.6	Limited subtype diversity
[2]	GAN-based image augmentation	Private Breast Cancer Dataset	89.2	Limited diversity in synthetic data
[3]	Ensemble of CNN and RF	Public and Private Datasets	93	Ensemble complexity and interpretability
[4]	Hybrid LBP and deep learning	Breast Cancer Dataset B	92.5	Small sample size
[5]	Transfer learning with CNN	Public Mammography Dataset	96.8	Limited annotations for abnormal findings
[6]	Ensemble of CNN and SVM	Private Hospital Dataset	94.3	Variability in image quality
[7]	Deep CNN with attention	BCDD Mammography Dataset	89.7	Limited generalizability
[8]	Transfer learning and ensemble approach	UK NHS Dataset	93.5	Imbalanced class distribution
[9]	Transfer learning with GAN-generated data	Synthetic Mammogram Dataset	89.8	Domain adaptation limitations
[10]	Deep CNN with attention and LBP fusion	BCDD Mammography Dataset	92.1	High computational complexity
[11]	Hybrid CNN and SVM with data augmentation	Hospital Dataset	87.9	Class imbalance
[12]	Fusion of handcrafted and deep features	INbreast Dataset	88.6	Complexity of hybrid feature extraction

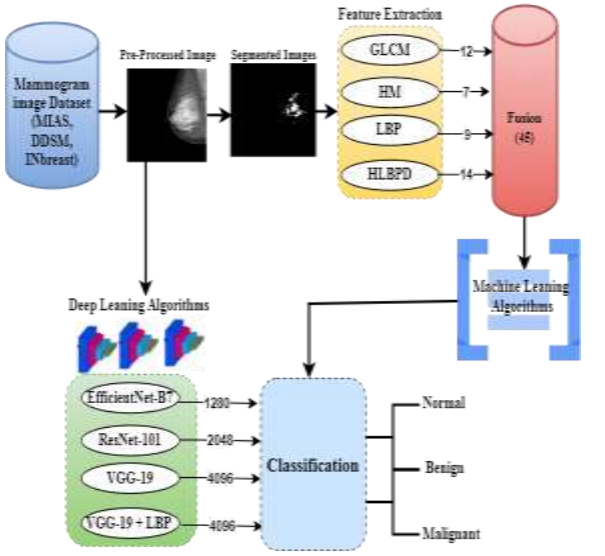

Figure 1. *Multimodal Approach for Breast Cancer Diagnosis: Image Pre-Processing, Segmentation, and Classification*

identification of breast cancer disease classification, as illustrated in the figure 1.

The initial step involved optimizing images by eliminating noise and enhancing edge contrast. Subsequently, a segmentation process was applied to segment the pre-processed images. These segmented images were then subjected to four distinct feature extraction methods: GLCM, HM, LBP, and the proposed HLBPD algorithm. The extracted features were used in various combinations for classification to diagnose breast cancer, employing machine learning (ML) algorithms like SVM, KNN, DT, NB, as well as deep learning algorithms including EfficientNet-B7, ResNet-101, VGG-19, and VGG-19 + LBP models. The assessment encompassed multiple datasets - MIAS, DDSM, and INbreast and the process concluded with a thorough comparison of algorithmic performance, assessed using a diverse set of metrics.

3.1 Dataset description

The table 2 provides a concise overview of three different datasets used for breast cancer detection. It includes information on the total number of images in each dataset, the number of classes or categories present, and the count of augmented images after applying data augmentation techniques.

Figure 2 illustrates representative samples of mammograms from different databases. In panel (1), examples from the MIAS database are shown, while panel (2) displays samples from the DDSM database. Panel (3) presents mammogram samples sourced from the INbreast database. This visual representation provides an overview of the diverse datasets used in the study, showcasing the variations in mammogram images obtained from different sources.

3.2 Preprocessing

Mammogram image preprocessing is a vital process in optimizing images to facilitate subsequent model development. In this study, separate preprocessing approaches were used to boost model performance and computational efficiency. The procedure begins with the loading of mammogram images, which are then handled with an Adaptive Directional Filter (ADF) for improved noise reduction and smoothing. These images are then partitioned into overlapping components with dimensions NxN. Each of these blocks performs Contrast Limited Adaptive Histogram Equalization (CLAHE) to improve contrast. The constructed image seamlessly includes these optimized blocks, which leads to smooth blending in overlapping areas. Another potential use of the ADF assists to noise reduction. The denoised image is then distinctly exhibited, demonstrating the method's disruptive ability to effectively remove noise and unwanted artifacts from medical images. Notably, this methodology differs from typical filtering approaches in that it selectively addresses noise and artifacts while maintaining the image's intrinsic properties. Figure 3 showcases the image enhancement process for a mammogram image. Figure 3a displays the initial noisy input image, while Figure 3b presents the de-noised version. Figure 3c exhibits the image after contrast enhancement. This progression demonstrates the success of the strategies used in reducing noise and enhancing image quality. This paper presents an Adaptive Hampel Identifier (AHI) technique for robust noise and artifact reduction. In contrast to classic methods such as the Hampel Identifier (HI), AHI takes a bidirectional approach, rapidly processing the image data while adapting its two-dimensionality.

Table 2. *Dataset Description*

Dataset	Total Images	Image Size	Format	Abnormalities	Normal	Benign	Malignant
MIAS	326	1024x1024	PGM	110 (Images)	207	67	52
DDSM	1232		JPEG	-	634	598	
INbreast	410			116 (Images)		41	75

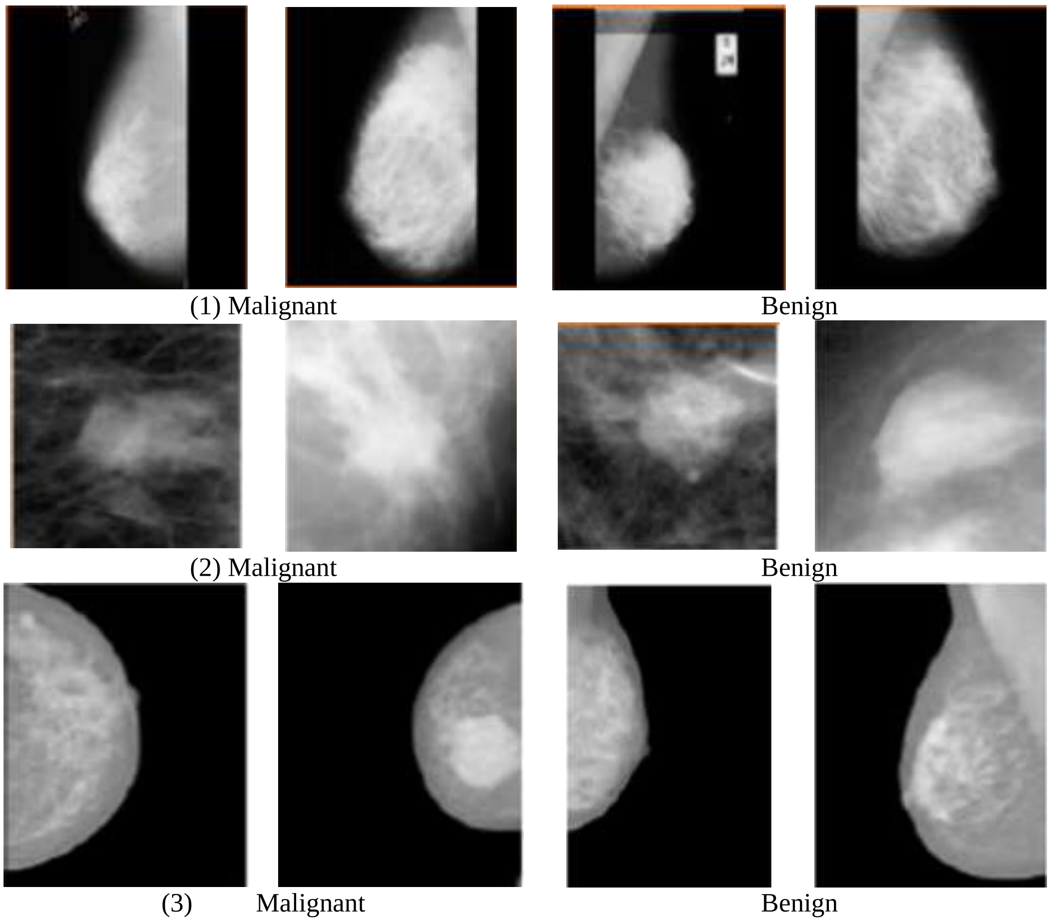

Figure 2. *Mammogram samples: (1) MIAS database; (2) DDSM database; (3) INbreast database*

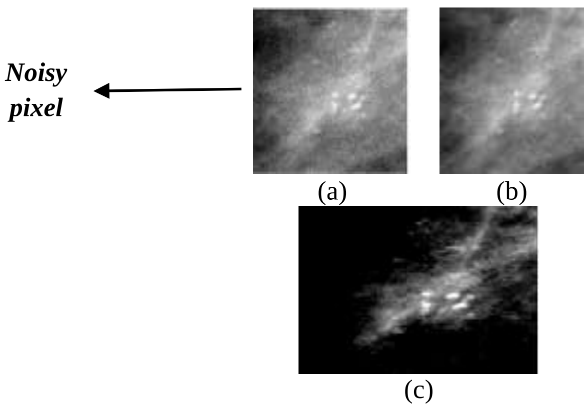

Figure 3. *(a) Noisy input image (b) De-noised image (c) Contrast enhanced image*

This moves from 1D to 2D window analysis broadens its application in image processing, demonstrating the work's novel methodology.

3.3 Segmentation

The suggested method uses a CTGA (CT-based Genetic Algorithm) segmentation methodology to detect breast cancer in mammography images. This novel technique combines CT image decomposition with GA optimization to determine the most effective feature set for adequately discriminating between positive and negative pixels. The method consisting of numerous steps: Initially, a fitness function f(X) is defined.

Table 3. *Features Description*

Feature Type	Description	Example Methods
Color Features	Represent color distribution and intensity in the image.	Color Histograms, Color Moments
Texture Features	Capture patterns and variations in texture.	Local Binary Pattern (LBP), GLCM, Gabor Filters
Shape Features	Describe the shapes and contours of objects.	Hu Moments, Zernike Moments, Contour Descriptors
Statistical Features	Calculate statistics like mean, variance, skewness, etc.	Mean, Variance, Skewness, Kurtosis
Frequency Domain Features	Derived from frequency analysis, revealing spatial frequency patterns.	Fourier Transform; Discrete Wavelet Transform

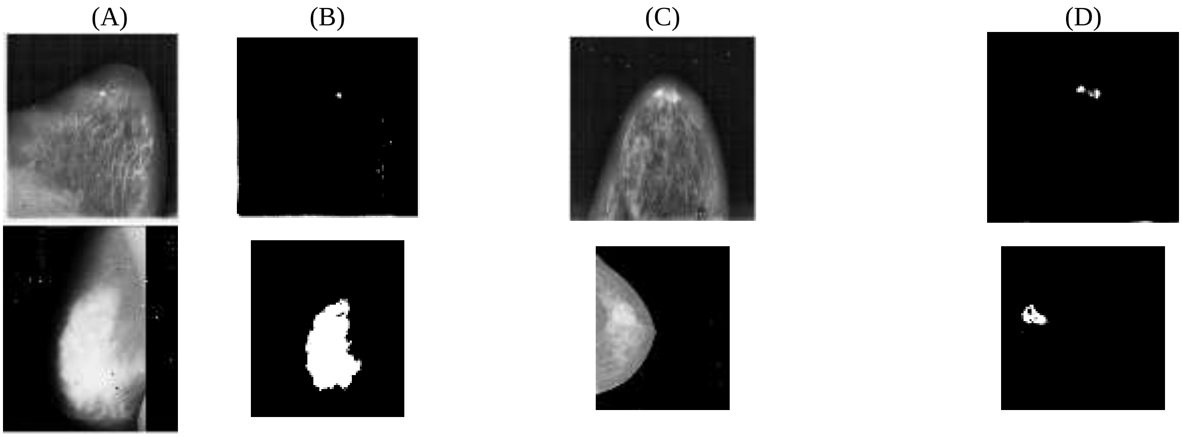

Figure 4. *(A, C) Original Images and (B, D) segmented images*

Then, a population of prospective solutions is created, followed by the selection of the best individuals. New offsprings are produced through the process of combining and mutation. This freshly formed progeny replaces the population's least suited individuals, and the cycle repeats until a predefined stopping point is reached. The implementation of the CT-based GA model in image segmentation has produced promising results, highlighting its potential to improve the accuracy and efficiency of breast cancer diagnosis in mammography images.

Figure 4 depicts a series of paired images illustrating the process of segmentation. In panels (A) and (C), the original images are showcased, providing an initial visual representation. Panels (B) and (D) display the corresponding segmented images, highlighting the outcome of the segmentation process. This visual presentation effectively contrasts the original images with their segmented counterparts, offering a clear visual understanding of the segmentation technique's impact on the images.

3.4 Feature Extraction

Feature extraction is the process of identifying and translating essential information from segmented images into an analytical and modeling-ready state. In image analysis, features describe image characteristics that are used to determine the difference between different objects, textures, or patterns. These attributes are then fed into various machine learning and classification algorithms. Features broadly categorized into various types are shown in Table 3. Color features include color spaces and histograms; texture features include LBP, Haralick features, and Gabor filters; shape features include moment-based descriptors and contour methods; statistical features include mean, variance, skewness, and kurtosis; and frequency domain features use Fourier Transform and Discrete Wavelet Transform. Integrating these strategies into breast cancer detection research improves the separation of malignant and non-cancerous instances in mammography pictures, increasing classification model accuracy.

Gray-Level Co-occurrence Matrix (GLCM)

GLCM is an effective approach for extracting texture information from pictures, especially mammograms. It measures the spatial correlations between pairs of pixels using their gray-level values. GLCM is frequently generated using precise offsets that specify the distance and direction between pixel pairs. Here's the basic equation for calculating the GLCM for a given offset (d_x, d_y) in a grayscale image I with gray levels ranging from 0 to $L-1$:

$$\mathrm{GLCM}(i,j,d_x,d_y) = \sum_{x=0}^{W-1}\sum_{y=0}^{H-1} \delta(I(x,y)-i)\cdot\delta(I(x+d_x,y+d_y)-j).$$

Where:

- i and j are the gray levels of the pixel pairs.
- d_x and d_y are the horizontal and vertical offsets.
- W and H are the width and height of the image, respectively.
- $\delta(x)$ is the Kronecker delta function, equal to 1 if $x = 0$ and 0 otherwise.

Once the GLCM is calculated, various texture features can be extracted from it. Table 4 shows some common texture features derived from the GLCM.

Hu Moments (HM) Feature Extraction Algorithm

The Hu Moments Feature Extraction Algorithm computes a set of seven Hu Moments from a grayscale image. It involves following key steps:

Algorithm:

Input: Grayscale image I of dimensions $M \times N$.
Output: Set of seven Hu Moments H_1 through H_7.

Step 1: Calculate Central Moments
For each pixel (x, y) in the image:

- Calculate intensity $I(x, y)$
- Calculate centroid: $\underline{x}, \underline{y}$
- Calculate central moments μ_{pq} with respect to centroid

Step 2: Normalize Central Moments
Normalize by μ_{00}:

$$\nu_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\left(1+\frac{p+q}{2}\right)}}$$

Step 3: Compute Hu Moments

Use v_{pq} to compute H_1 through H_7:

$$H_1 = \nu_{20} + \nu_{02}$$
$$H_2 = (\nu_{20} - \nu_{02})^2 + 4 \cdot \nu_{11}^2$$
$$H_3 = (\nu_{30} - 3 \cdot \nu_{12})^2 + (3 \cdot \nu_{21} - \nu_{03})^2$$
$$H_4 = (\nu_{30} + \nu_{12})^2 + (\nu_{21} + \nu_{03})^2$$
$$H_5 = (\nu_{30} - 3 \cdot \nu_{12}) \cdot (\nu_{30} + \nu_{12}) \left[(\nu_{30} + \nu_{12})^2 - 3 \cdot (\nu_{21} + \nu_{03})^2\right]$$
$$+ (3 \cdot \nu_{21} - \nu_{03}) \cdot (\nu_{21} + \nu_{03}) \left[3 \cdot (\nu_{30} + \nu_{12})^2 - (\nu_{21} + \nu_{03})^2\right]$$
$$H_6 = (\nu_{20} - \nu_{02}) \left[(\nu_{30} + \nu_{12})^2 - (\nu_{21} + \nu_{03})^2\right]$$
$$+ 4 \cdot \nu_{11} \cdot (\nu_{30} + \nu_{12}) \cdot (\nu_{21} + \nu_{03})$$
$$H_7 = (3 \cdot \nu_{21} - \nu_{03}) \cdot (\nu_{30} + \nu_{12}) \left[(\nu_{30} + \nu_{12})^2 - 3 \cdot (\nu_{21} + \nu_{03})^2\right]$$
$$- (\nu_{30} - 3 \cdot \nu_{12}) \cdot (\nu_{21} + \nu_{03}) \left[3 \cdot (\nu_{30} + \nu_{12})^2 - (\nu_{21} + \nu_{03})^2\right]$$

Step 4: Output

Return H_1 through H_7 as the feature vector.

The Hu Moments algorithm captures shape characteristics invariant to translation, rotation, and scale changes, and is useful for image analysis tasks, including features extraction from mammogram images for breast cancer detection.

Local Binary Pattern (LBP) Algorithm
The LBP algorithm is a texture analysis tool for image processing. It stores local patterns around each pixel by comparing its intensity to nearby pixels, resulting in a binary representation that captures complex texture changes. LBP has applications in a variety of industries, including mammography image analysis for improved feature extraction and pattern recognition.

Algorithm:

Input: Grayscale mammogram image I of dimensions $M \times N$.
Output: LBP-encoded image L of the same dimensions.
Step 1: LBP Calculation for Each Pixel
For each pixel (x, y) in the image:

1. Define a circular neighborhood around the central pixel with radius r and P equally spaced sampling points on the circumference.
2. Calculate the threshold value T using the intensity of the central pixel: $T = I(x, y)$.

Table 4. *Feature Description derived from GLCM*

Feature	Description
Contrast	Measures intensity differences between neighboring pixel pairs.
Energy (Angular Second Moment)	Reflects pixel pair uniformity.
Entropy	Quantifies pixel pair randomness.
Homogeneity (Inverse Difference Moment)	Gauges uniformity by pixel pair proximity to the diagonal.
Correlation	Indicates linear relationships between pixel pairs.
Dissimilarity	Measures variations in pixel intensity.
Angular Second Moment (ASM)	Captures overall pixel pair uniformity.
Maximum Probability	Represents the most common pixel pair occurrence.
Cluster Shade	Measures the distribution's skewness.
Cluster Prominence	Highlights distribution asymmetry.
Sum of Squares Variance	Quantifies variation in pixel pair intensity.
Inverse Difference Normalized (IDN)	Measures normalized pixel pair similarity.

3. Compare the intensity values of the P sampling points in the neighborhood with the threshold T.
   - If $I(x_p, y_p) \geq T$ for a sampling point (x_p, y_p), assign a value of 1.
   - If $I(x_p, y_p) < T$, assign a value of 0.
4. Concatenate the binary values in clockwise order to form a P- bit binary number. This binary number represents the local pattern around the central pixel.

5. Convert the binary number to decimal to obtain the LBP value for the central pixel.

LBPs have ability to encode local variations efficiently makes it indispensable in diverse applications, including medical image analysis such as mammogram interpretation for detecting complex structures and abnormalities.

Proposed: Hybrid LBP-Deep (HLBPD) Feature Fusion Algorithm

The Proposed HLBPD algorithm presents a novel approach to mammogram image analysis. By combining Local Binary Pattern (LBP) texture features with deep learning insights, it harnesses the complementary strengths of both techniques to enhance breast cancer detection accuracy, demonstrating the potential for improved diagnostic outcomes.

Algorithm: Hybrid LBP-Deep Feature Extraction

Input:

- **Mammogram images dataset (with associated labels)**
- **Pre-trained deep learning model**
- **Parameters for LBP (radius, neighbors)**
- **Parameters for SVM or KNN classifiers (depending on choice)**

Function calculate_LBP_value (center pixel, neighbor pixels):
```
    lbp_value = 0
    For neighbor pixel in neighbor pixels:
        If neighbor pixel >= center pixel:
            lbp_value += 2^(neighbor pixel - center pixel)
    Return lbp_value
```

Function extract_LBP_features(image):
```
    Initialize histogram array
    For pixel in image:
        center pixel = image[pixel]
        neighbor pixels = [image[neighbor] for neighbor in neighbors]
        lbp_value = calculate_LBP_value (center pixel, neighbor pixels)
        Increment histogram array[lbp_value]
    Normalize histogram array
    Return normalized histogram
```

Function extract_deep_features (image, pre-trained model):
```
    preprocessed image = preprocess(image)
    deep features = pre-trained model (preprocessed image)
    Return deep features
```

Function concatenate features (lbp_features, deep features):
```
    concatenated features = concatenate (lbp_features, deep features)
    Return concatenated features
```

Function train classifier (features, labels):
```
    classifier = SVM () or KNN ()
    trained classifier = classifier. Fit (features, labels)
    Return trained classifier
```

Main process:
```
Initialize empty feature list and label list
For mammogram image in dataset:
    lbp_features = extract_LBP_features (mammogram image)
    deep features = extract_deep_features (mammogram image, pre-trained model)
    concatenated features = concatenate features (lbp_features, deep_features)
    Append concatenated features and label to feature list and label list

trained classifier = train classifier(feature_list, label list)
```

The Hybrid LBP-Deep Feature Extraction technique combines LBP texture features with deep learning insights for mammography image analysis. It uses pre-trained deep models and LBP parameters to extract and normalize LBP patterns. These patterns are then concatenated with deep features, and the combined features are used to train machine learning classifiers. This combination of texture and semantic information improves accuracy and robustness in breast cancer diagnosis, making it an effective tool for medical image categorization.

3.5 Classification

In the classification process, incorporating LBP features and deep learning insights improves the accuracy and efficiency of mammography image analysis. These models use both handcrafted LBP patterns and learned deep features to produce more accurate and robust classifications. This study advances early breast cancer diagnosis by combining many methodologies, with the potential to improve patient outcomes and healthcare systems.

4. Results and Discussion

This paper introduces a novel approach that combines local binary pattern (LBP) features and features automatically extracted from seven deep learning models, including EfficientNet-B7, ResNet-101, VGG-19, and VGG-19 + LBP models. The datasets used are MIAS, DDSM, and INbreast. The DL classifiers trained on this feature combination consistently outperformed existing state-of-the-art models across multiple metrics, demonstrating the hybrid approach's potential to improve classification tasks by effectively combining different feature extraction methods and classifier types. The proposed model was evaluated using MATLAB 2018B, executed on a system powered by an Intel i7 CPU, equipped with a 2TB hard disk, 8GB RAM, and running the Windows 10 operating system.

4.1 Results for DL models

The results outline the performance of DL models in various tasks. These outcomes encompass metrics such as accuracy, loss, precision, recall, and F1-Score, revealing the efficacy of different deep learning architectures across different datasets.
Based on this comparative analysis, the "VGG-19 + LBP" model consistently demonstrates high performance across all datasets in terms of accuracy, precision, recall, and F1 score. It achieves the highest overall scores on MIAS and DDSM datasets and maintains competitive performance on the INbreast dataset. EfficientNet-B7 also shows good performance, particularly on the INbreast dataset, while ResNet-101 exhibits varying performance with relatively lower precision and recall scores on some datasets. Please note that the above analysis assumes that the performance metrics are averaged across different classes or instances in the datasets. Additionally, these results are based on the provided values and may not accurately reflect the real-world performance of these models on medical image datasets. Cancer is studied and reported in the literature[13-20].

5. Conclusion

This study describes a unique methodology for leveraging the potential of LBP features in conjunction with features extracted from multiple DL models, such as EfficientNet-B7, ResNet-101, VGG-19, and the hybrid VGG-19 + LBP model. The study focuses on breast cancer categorization utilizing the MIAS, DDSM, and INbreast datasets. This combination of feature extraction techniques and classifier types demonstrates the potential for more advanced classification challenges. Finally, our study demonstrates the feasibility of combining LBP features with DL models for robust breast cancer classification. The hybrid VGG-19 + LBP model's superior accuracy and consistent performance across varied datasets demonstrate its potential for improving medical image processing, leading to better diagnosis and patient care.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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