A Novel Fuzzy Fusion-Based Segmentation with Enhanced Feature Selection for Improved Breast Cancer Detection

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Abstract – This paper presents a hybrid methodology for breast cancer detection by leveraging fuzzy fusion-based segmentation, advanced feature extraction, and ensemble learning. The approach employs a novel fuzzy fusion-based segmentation framework was proposed, combining three segmentation techniques—threshold-based segmentation using Rényi Entropy, region-based segmentation using the Level Set Method, and semantic segmentation with DeepLab v3+. This fusion approach effectively captured both fine-grained details and larger pathological regions. Features extracted from these segmented regions included Multi-Scale Local Binary Patterns (MSLBP), Maximally Stable Extremal Regions (MSER), and AlexNet-based deep features. To optimize feature selection, the Enhanced Snake Optimization (ESO) algorithm is applied, selecting the most relevant features while reducing redundancy. For classification, the Ensemble AdaBoost Classifier is used, combining multiple weak classifiers to improve performance by focusing on difficult instances. Experimental results show that the proposed hybrid methodology outperforms traditional approaches, offering superior classification accuracy, sensitivity, and specificity. The method demonstrates the effectiveness of combining advanced feature extraction and ensemble learning for reliable and accurate breast cancer detection.
Keywords – AdaBoost, AlexNet, DeepLab v3+, ESO, Level Set Method, MSER, MSLBP.

I. INTRODUCTION

Breast cancer remains one of the most prevalent and challenging health concerns worldwide, with significant impacts on both morbidity and mortality rates. Early detection and accurate diagnosis are critical in improving survival rates, making the development of advanced diagnostic systems imperative. Traditional diagnostic methods, including manual examination and basic imaging techniques, often suffer from limitations in terms of accuracy and the ability to detect subtle abnormalities. As a result, there is a pressing need for more robust and efficient systems capable of handling the complexities of medical image data to provide early and precise diagnoses.

In recent years, deep learning and artificial intelligence (AI) have emerged as powerful tools in the field of medical image analysis. By leveraging large datasets and sophisticated algorithms, these technologies can automatically identify and classify patterns in medical images that are otherwise difficult for human experts to detect. However, despite their

promising potential, current methods still face challenges in the form of high-dimensional feature extraction, variability in image quality, and the need for improved segmentation accuracy. These challenges hinder the development of truly reliable systems for breast cancer diagnosis, necessitating the exploration of novel methodologies that address these gaps.

To overcome these limitations, this research focuses on enhancing the segmentation, feature extraction, and classification components of breast cancer diagnostic systems. Traditional segmentation techniques, which isolate regions of interest (ROI) in medical images, often fail to generalize across different imaging modalities, leading to errors in detecting tumor boundaries. Additionally, feature extraction models based on handcrafted techniques or limited deep learning architectures often overlook the rich texture and structural patterns present in the breast tissue, which are essential for accurate classification. These shortcomings highlight the need for more adaptable and comprehensive approaches to segmentation and feature extraction. This paper proposes a novel methodology that integrates multiple segmentation techniques to improve robustness and accuracy in isolating diagnostically significant regions. Specifically, a fuzzy fusion-based segmentation model is introduced, which combines threshold-based, region-based, and deep learning-based methods to achieve more reliable results across varying image qualities and modalities. Furthermore, the feature extraction framework proposed in this study incorporates a combination of traditional and deep learning-based methods, including Multi-Scale Local Binary Patterns (MSLBP), Maximally Stable Extremal Regions (MSER), and AlexNet-based deep features, to capture a more comprehensive range of tissue patterns. This integrated approach ensures that both texture and structural features are effectively utilized, thereby improving classification accuracy.

The motivation for employing these advanced methods stems from the desire to develop a more robust and adaptable diagnostic system capable of handling the complexity and variability inherent in breast cancer imaging data. Specifically, the fuzzy fusion-based segmentation approach is chosen to overcome the limitations of single segmentation techniques, while the combination of deep learning and traditional feature extraction methods allows for a more holistic representation of breast tissue patterns. Furthermore, the use of an optimized feature selection mechanism, based on the Enhanced Snake Optimization Algorithm, ensures that only the most relevant features are retained, reducing computational complexity and improving classification performance. Finally, the classification process is enhanced using an AdaBoost classifier, which is known for its ability to combine multiple weak learners into a strong predictive model, offering improved accuracy and robustness in handling the variability of breast cancer images.

This paper addresses the critical issue of enhancing the robustness and accuracy of breast cancer diagnostic systems by proposing a comprehensive framework that combines advanced segmentation, feature extraction, and classification techniques. The key contributions of this research are as follows:

- ***Fuzzy Fusion-based Segmentation:*** A novel segmentation method is introduced that integrates multiple techniques to improve the accuracy and reliability of region-of-interest isolation in breast cancer images.
- ***Comprehensive Feature Extraction Framework:*** The paper presents an advanced feature extraction pipeline that combines traditional methods like MSLBP and MSER with deep learning-based features from AlexNet, ensuring a more holistic and effective representation of tissue patterns.

- ***Optimized Feature Selection:*** The use of the Enhanced Snake Optimization Algorithm is proposed for selecting the most relevant features from high-dimensional data, reducing complexity and improving classification performance.
- ***AdaBoost Classification:*** An AdaBoost classifier is employed to enhance the accuracy and robustness of the diagnostic system by combining multiple weak learners into a strong predictive model.

The remainder of the paper is structured as follows. Section II reviews relevant literature and previous works in the field of breast cancer diagnosis, highlighting the limitations of existing methods. Section III outlines the proposed methodologies used in this study, including detailed descriptions of the proposed segmentation, feature extraction, and classification approaches. Section IV presents the experimental results and discusses the performance of the proposed system in comparison to existing methods. Finally, Section V concludes the paper and suggests potential directions for future research.

II. Literature Review

The authors of [1] applied Support Vector Machines (SVM) and Artificial Neural Networks (ANN) in the WEKA environment using the Wisconsin Breast Cancer dataset. Their comparison of performance metrics—such as accuracy, precision, sensitivity, and ROC area—showed that SVM (SMO algorithm) outperformed other methods. The authors of [2] focused on automatic breast cancer diagnosis through machine learning algorithms, demonstrating that combining feature-based preprocessing methods with classification algorithms yields improved diagnostic results.

The authors of [3] aimed to identify prognostic factors for survival in breast cancer patients by utilizing several machine learning algorithms, including Support Vector Machine, Random Tree, Artificial Neural Networks, Extreme Gradient Boosting, Logistic Regression, and Decision Tree. The study found that Random Forest delivered slightly better performance, although all methods produced similar accuracy values.

In the study by [4], a variety of machine learning techniques—such as Naive Bayes, Random Forest, AdaBoost, SVM, Least Squares SVM, Adabag, Logistic Regression, and Linear Discriminant Analysis—were applied to predict breast cancer survival and metastasis. The authors of [5] focused specifically on predicting metastasis using machine learning, identifying Random Forest as the most suitable method for forecasting metastasis at least three months in advance.

The authors of [6] explored machine learning, deep learning, and word embedding methods to create a recommendation system that supports physician decision-making in breast cancer diagnosis. In [7], deep neural networks (DNNS) with support vector values were used to achieve superior results compared to existing methods. The authors of [8] examined the use of machine learning for computer-aided diagnosis of breast cancer using histopathological data and highlighted the increasing reliance on deep learning models in recent studies.

Breast cancer arises from mutations in genes responsible for regulating cell growth, leading to uncontrolled cell division. Tumors may be benign or malignant. Benign tumors grow slowly, do not spread, and are not considered cancerous, whereas malignant tumors multiply rapidly and can spread throughout the body [9], [10]. Early diagnosis is critical to improving survival rates, but manual diagnosis can be prone to errors, prompting the need for automated decision support systems [11], [12]. Machine learning offers a promising solution for analyzing large

datasets—such as medical history, mammographic images, and histopathology data—to assist in early breast cancer detection [13].

The Wisconsin Breast Cancer Diagnostic (WBCD) dataset is widely used in studies employing machine learning for breast cancer detection. This dataset contains digitized features from fine-needle aspiration (FNA) biopsies. The authors of [14] achieved the highest classification accuracy of 96.7% with W-KNN when comparing various algorithms, including SVM, Logistic Regression (LR), K-Nearest Neighbors (KNN), Weighted KNN, and Gaussian Naïve Bayes. In [15], the authors applied Principal Component Analysis (PCA) to reduce dimensionality and clean outliers, achieving an accuracy of 98.9% using W-KNN. The authors of [16] used deep neural networks (DNN) with ReLU activation and Adagrad optimizer, obtaining a classification accuracy of 97.94%. The authors of [17] found that KNN and Random Forest methods produced comparable results, with an accuracy of 97.14%, while [18] achieved 93.9% accuracy using Logistic Regression.

Other studies, such as [19], [20], and [21], explored ensemble learning techniques, deep learning models (e.g., Long Short-Term Memory), and hyperparameter optimization, achieving accuracies ranging from 90% to 99.1%. The authors of [22] demonstrated the use of LSTM in achieving a high classification accuracy of 99.1%, while [23] reported varying accuracy rates of 90.64%, 84.80%, and 92.98% using KNN, Naïve Bayes, and SVM algorithms, respectively.

- ***Research Gap:*** While various machine learning techniques have shown promise for breast cancer detection, existing studies predominantly focus on isolated segmentation, feature extraction, or classification methods, often overlooking the potential of integrating these components into a unified, hybrid approach. Additionally, traditional methods tend to rely on single segmentation techniques or basic feature extraction methods, which may not fully capture the complex variations in tumor characteristics. Furthermore, many studies have not explored the synergy of advanced segmentation techniques (e.g., threshold-based, region-based, and semantic segmentation) with state-of-the-art feature extraction methods like MSLBP, MSER, and deep features from models like AlexNet. Finally, although ensemble learning techniques like AdaBoost have been used in cancer diagnosis, they often fail to leverage optimized feature selection processes, leading to potential inefficiencies in handling redundant or irrelevant features. The proposed methodology in this paper addresses these gaps by combining fuzzy fusion-based segmentation, advanced feature extraction, and Enhanced Snake Optimization (ESO) for optimal feature selection. This hybrid approach, integrated with an Ensemble AdaBoost classifier, offers the potential to significantly improve the accuracy, sensitivity, and specificity of breast cancer detection, providing a more comprehensive and robust solution compared to traditional methods.

III. PROPOSED METHODOLOGY

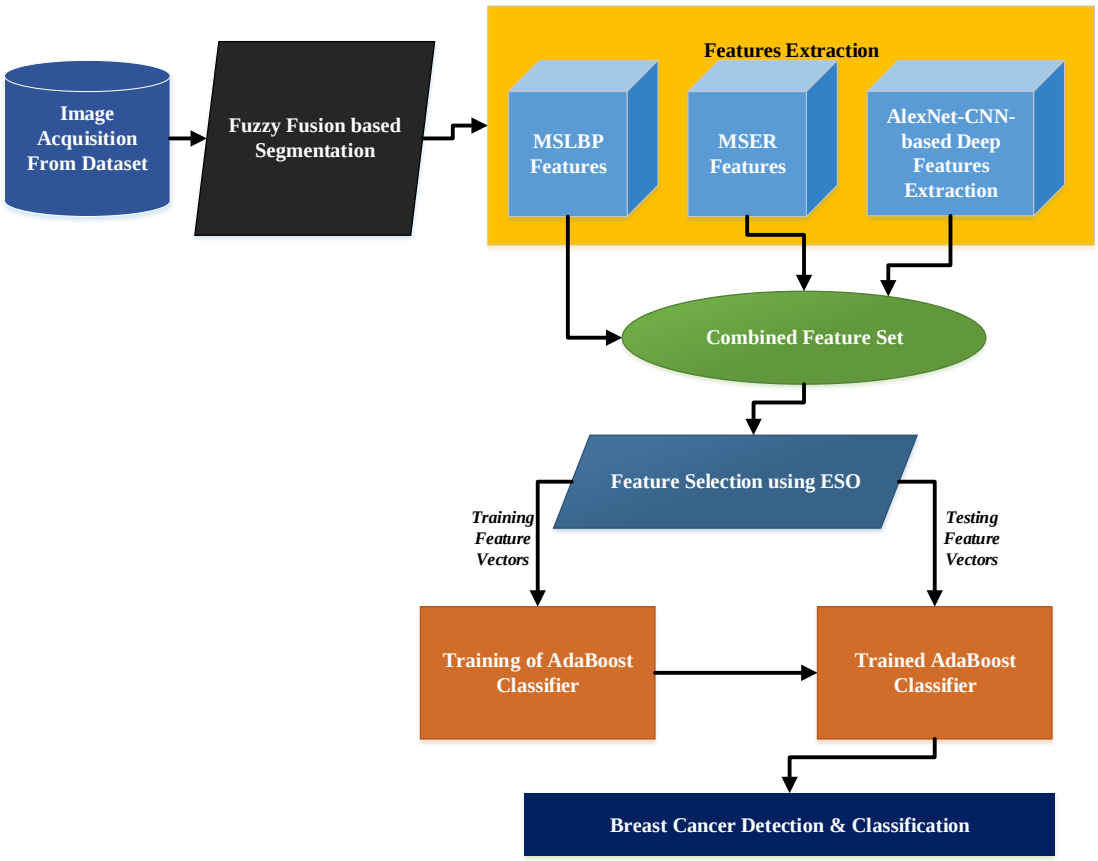


Figure 1: Flow Diagram for Proposed Fuzzy Fusion-Based Breast Cancer Detection Method

The proposed methodology shown in Figure 1 for breast cancer detection integrates multiple imaging modalities, segmentation techniques, and classification approaches. The process begins with acquiring breast images from ultrasound, mammography, and thermography. These images undergo preprocessing for quality consistency, followed by segmentation using a novel fuzzy fusion approach. This approach combines threshold-based segmentation (Rényi entropy), region-based segmentation (level set method), and DeepLab v3+ semantic segmentation to isolate the region of interest (ROI) accurately.

After segmentation, feature extraction is performed using Multi-Scale Local Binary Patterns (MSLBP), Maximally Stable Extremal Regions (MSER), and deep features from AlexNet. These features are combined into a comprehensive vector. To reduce dimensionality, the Enhanced Snake Optimization Algorithm is applied for feature selection, ensuring that only the most relevant features are retained.

Finally, the selected features are classified using the AdaBoost classifier, which combines multiple weak learners to provide a robust predictive model. This methodology improves segmentation, enhances feature extraction, and optimizes classification, offering a reliable system for breast cancer detection.

3.1 Image Acquisition from the Dataset

Diagnostic images are obtained from datasets containing ultrasound (US), mammography (MG), and thermography (TG) images for breast cancer detection. The acquired image data I is represented as:

$$I_{n,m,c} \in \mathbb{R}^{H \times W \times C} \tag{1}$$

Where H and W are the image dimensions, and C is the number of channels. The images are from various sources:

- Ultrasound (I_{US}): Tissue reflectivity with speckle noise.
- Mammography (I_{MG}): High contrast for dense tissues.
- Thermography (I_{TG}): Infrared images showing temperature variations.

3.2 Fuzzy Fusion-Based Segmentation

Segmentation is crucial in breast cancer detection for isolating significant regions. The proposed fuzzy fusion-based segmentation combines three methods:

- Threshold-based segmentation using Rényi entropy
- Region-based segmentation using the level set method
- DeepLab v3+ architecture-based semantic segmentation

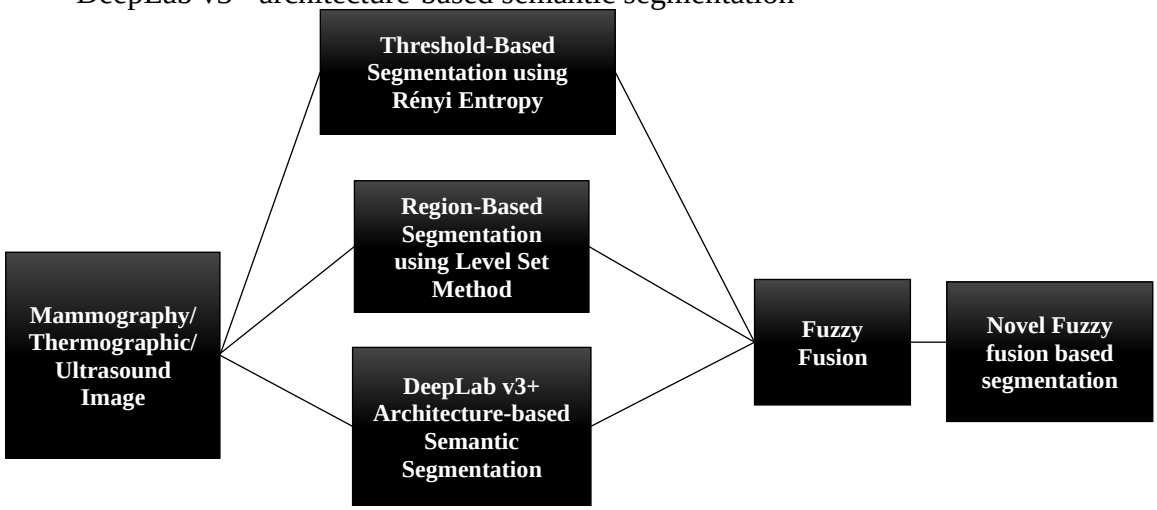


Figure 2: Proposed flow diagram of novel fuzzy logic based image segmentation for region of interest system architecture

This approach leverages the strengths of each technique to enhance robustness and accuracy. The final segmentation is achieved by applying a fuzzy logic framework, which assigns optimal weights to each method based on its contribution to isolating the region of interest (ROI) (Figure 2).

3.2.1 Threshold-Based Segmentation Using Rényi Entropy

Threshold-based segmentation divides an image into foreground and background regions by selecting an optimal threshold. In this chapter, Rényi entropy, an extension of Shannon entropy, is used to compute this threshold. It is particularly effective for breast cancer imaging as it captures detailed intensity distributions across different modalities.

Let the input image be I with intensity levels $L = \{0,1, \dots ,255\}$. The histogram $p(l)$ represents the probability of intensity level l in the image:

$$p_l = \frac{n_l}{N}, \quad \sum_{l=0}^{255} p(l) = 1 \tag{2}$$

Where n_l is the number of pixels with intensity l, and N is the total number of pixels.
Rényi entropy for a threshold T is computed for two regions:

1. $R_1 = \{0,1,\dots,T\}$: Foreground region.
2. $R_2 = \{T+1, T+2, \dots, 255\}$: Background region.

The entropy for each region is given as:

$$H_\alpha(R_1) = \frac{1}{1-\alpha}\log\left(\sum_{l\in R_1} p(l)^\alpha\right), \quad H_\alpha(R_2) = \frac{1}{1-\alpha}\log\left(\sum_{l\in R_2} p(l)^\alpha\right) \tag{3}$$

Where $\alpha > 0$ is the Rényi entropy parameter, controlling the sensitivity of the entropy measure.
The total Rényi entropy for a threshold T is:

$$H_\alpha(T) = H_\alpha(R_1) + H_\alpha(R_2) \tag{4}$$

The optimal threshold T^* is the value that maximizes $H_\alpha(T)$:

$$T^* = \arg\max_T H_\alpha(T) \tag{5}$$

The segmentation mask $S_{\text{Rényi}}(i,j)$ is generated as:

$$S_{\text{Rényi}}(i,j) = \begin{cases} 1 & if\ I(i,j) \geq T^* \\ 0 & if\ I(i,j) < T^* \end{cases} \tag{6}$$

This method is particularly effective for separating regions with distinct intensity levels, such as lesions and surrounding tissues.

3.2.2 Region-Based Segmentation Using the Level Set Method

The level set method is a region-based segmentation technique that evolves a curve to identify object boundaries based on intensity and gradient properties, making it effective for delineating lesions with irregular boundaries.
Let $\phi(x,y,t)$ represent the level set function at time t, where:

- $\phi(x,y,t) > 0$: Points inside the curve.
- $\phi(x,y,t) = 0$: Points on the curve (contour).
- $\phi(x,y,t) < 0$: Points outside the curve.

The evolution of ϕ is governed by the level set equation:

$$\frac{\partial \phi}{dt} + F|\nabla\phi| = 0 \tag{7}$$

Where F is the speed function, and $\nabla\phi$ is the gradient of ϕ.
The speed function F incorporates image intensity $I(x,y)$ and curvature κ:

$$F = \lambda_1(I-\mu_1)^2 - \lambda_2(I-\mu_2)^2 + \upsilon\kappa \tag{8}$$

Where:

- μ_1 and μ_2: Mean intensities of the regions inside and outside the curve, respectively
- λ_1 and λ_2: Weighting parameters
- ν: Weight for the curvature term

The segmented output $S_{\text{LevelSet}}(i,j)$ is derived from the zero level of φ:

$$S_{\text{LevelSet}}(i,j) = \begin{cases} 1 & if\ \phi(i,j,t) \geq 0 \\ 0 & if\ \phi(i,j,t) < 0 \end{cases} \tag{9}$$

This method adapts to local intensity variations, making it robust for segmenting lesions with complex boundaries.

3.2.3 DeepLab v3+ Architecture-based Semantic Segmentation for ROI

DeepLab v3+ is used for segmenting the region of interest (ROI). The input image I is:

$$I \in \mathbb{R}^{H \times W \times C} \tag{10}$$

Atrous Convolution helps capture multi-scale features:

$$y[i] = \sum_{k=1}^{K} x[i + r \cdot k] \cdot w[k] \tag{11}$$

Where:

- x is the input feature map.
- w are the convolutional weights.
- K is the filter size.
- r is the dilation rate.

Encoder (ASPP) extracts multi-scale features:

$$\text{ASPP}(f) = \{f_1, f_2, \dots, f_n\} \tag{12}$$

Where f_i is the feature map extracted at a specific scale using dilation rate r_i. The combined features are given by:

$$f_{ASPP} = \text{concat}(f_1, f_2, \dots, f_n) \tag{13}$$

Decoder refines the segmentation output:

$$O = \sigma(W * f_{ASPP} + b) \tag{14}$$

Where:

- W and b are the weights and biases.
- σ is the softmax activation function applied pixel-wise to produce class probabilities.

Final Mask for binary segmentation:

$$M_{final}(i,j) = \begin{cases} 1 & if\ P\big(I(i,j)\big) > T \\ 0 & otherwise \end{cases} \tag{15}$$

Where $P\big(I(i,j)\big)$ is the predicted probability for pixel (i,j).

ROI Extraction:

$$ROI(i,j) = I(i,j) \cdot M_{final}(i,j) \tag{16}$$

DeepLab v3+ enables precise segmentation and ROI extraction for breast cancer detection. It leverages atrous convolution and Atrous Spatial Pyramid Pooling (ASPP) to capture multi-scale contextual information and produces a segmentation mask S_{DeepLab}.

3.2.4 Fuzzy Fusion-Based Segmentation

The fuzzy fusion segmentation method combines the results of three distinct techniques: threshold-based segmentation using Rényi entropy, region-based segmentation via the level set method, and semantic segmentation with DeepLab v3+. This approach utilizes fuzzy logic to integrate these outputs, assigning confidence values to each method's result and producing a final, robust segmentation.

Segmentation Outputs: Let $S_{\text{Rényi}}$, S_{LevelSet}, and S_{DeepLab} represent the binary masks from the three segmentation methods, where each pixel (i,j) indicates whether it belongs to the region of interest (ROI):

$$S_k(i,j) \in \{0,1\}, \qquad k \in \{\text{Rényi}, \text{LevelSet}, \text{DeepLab}\} \tag{17}$$

Fuzzy Membership Functions: For each method k, a fuzzy membership function $\mu_k(i,j)$ quantifies the confidence that a pixel belongs to the ROI. These functions depend on criteria such as intensity, boundary smoothness, and gradient strength. The general form is:

$$\mu_k(i,j) = f\big(S_k(i,j), Q_k(i,j)\big) \tag{18}$$

- ***For Rényi Entropy:***

$$\mu_{\text{Rényi}}(i,j) = 1 - |I(i,j) - T^*| / \max(I) \tag{19}$$

  Where T^* is the optimal threshold and $I(i,j)$ is the pixel intensity.

- ***For Level Set Method:***

$$\mu_{\text{LevelSet}}(i,j) = \exp(-|\kappa(i,j)|) \tag{20}$$

  Where $\kappa(i,j)$ represents the curvature at pixel (i,j).

- ***For DeepLab v3+:***

$$\mu_{\text{DeepLab}}(i,j) = P_{ROI}(i,j) \tag{21}$$

  Where $P_{ROI}(i,j)$ is the probability that pixel (i,j) belongs to the ROI.

Fusion of Segmentation Results: The final fused segmentation mask $\mu_{\text{Fusion}}(i,j)$ is obtained by aggregating the membership values and segmentation masks from all methods:

$$\mu_{\text{Fusion}}(i,j) = \frac{\sum_k w_k \cdot \mu_k(i,j) \cdot S_k(i,j)}{\sum_k w_k \cdot \mu_k(i,j)} \tag{22}$$

Here, w_k is the weight of each method, based on its reliability:

$$w_k = \frac{Performance_{method\ k}}{\sum_k Performance_{method\ k}} \tag{23}$$

Defuzzification: The final binary segmentation mask $S_{\text{Final}}(i,j)$ is obtained by defuzzifying the aggregated fuzzy output $\mu_{\text{Fusion}}(i,j)$ with a threshold T_{Fusion}:

$$S_{\text{Final}}(i,j) = \begin{cases} 1 & if\ \mu_{\text{Fusion}}(i,j) \geq T_{\text{Fusion}} \\ 0 & f\ \mu_{\text{Fusion}}(i,j) < T_{\text{Fusion}} \end{cases} \tag{24}$$

This fusion framework effectively combines the strengths of multiple segmentation methods, resulting in a highly accurate and adaptive segmentation process for breast cancer detection.

3.3 Feature Extraction

Feature extraction transforms the fuzzy fusion-based segmented image into a set of features for classification. Three techniques are applied: Multi-Scale Local Binary Patterns (MSLBP), Maximally Stable Extremal Regions (MSER), and AlexNet-based deep features, each contributing distinct characteristics.

3.3.1 Multi-Scale Local Binary Patterns (MSLBP) Features

MSLBP captures texture patterns at multiple spatial scales, which is effective for breast cancer images. The basic LBP operator compares pixel intensities with their neighbors:

$$LBP_{P,R}(i,j) = \sum_{p=0}^{P-1} s\left(I_p - I_c\right) \cdot 2^p \tag{25}$$

Where:

- P: Number of neighbors.
- R: Radius of the neighborhood.
- I_c: Intensity of the center pixel.
- I_p: Intensity of the p^{th} neighboring pixel.
- $s(x)$: Sign function:

$$s(x) = \begin{cases} 1 & if\ x \geq 0 \\ 0 & if\ x < 0 \end{cases} \tag{26}$$

To capture multi-scale patterns, MSLBP is computed at various radii R_k:

$$MSLBP(i,j) = \bigcup_{k=1}^{K} LBP_{P,R_k}(i,j) \tag{27}$$

Where K is the number of scales, and R_k is the radius at scale k.

The texture feature is represented by the MSLBP histogram:

$$H_{MSLBP}(b) = \sum_{i,j} \delta\left(LBP_{P,R}(i,j) - b\right)$$
$$b \in \{0,1,\dots,2^{P-1}\} \tag{28}$$

3.3.2 Maximally Stable Extremal Regions (MSER) Features

MSER identifies stable regions in the image that are invariant to transformations. Let I represent the segmented image, and let $\mathcal{L}(t)$ denote the set of connected components obtained by thresholding I at intensity t:

$$\mathcal{L}(t) = \{R_1, R_2, \dots, R_k\} \tag{29}$$

Where R_k is a connected region with all pixel intensities greater than or equal to t.
The stability of each region is defined as:

$$\Delta(R) = \frac{|R_{t+\Delta} - R_t|}{|R_t|} \tag{30}$$

A region is maximally stable if:

$$R_{MSER} = \arg\min_t \Delta(R) \tag{31}$$

Geometric and intensity-based descriptors, such as area, perimeter, and mean intensity, are extracted to form the MSER feature vector.

3.3.3 AlexNet-Based Deep Features

AlexNet, a deep convolutional neural network (CNN), extracts hierarchical features from the segmented region. The ROI is resized to 227×227 and passed through the network, which includes five convolutional layers, each followed by max-pooling, and three fully connected layers. The output at each layer is the feature map f_l, defined by:

$$f_l = g(W_l * f_{l-1} + b_l) \tag{32}$$

Where W_l are the weights, b_l is the bias, and g is the activation function (ReLU). Max-pooling reduces spatial dimensions:

$$f_{pooled}(i,j) = \max_{p,q \in \text{window}} f(i+p, j+q) \tag{33}$$

Finally, the fully connected layers produce the deep feature vector:

$$F_{\text{AlexNet}} \in \mathbb{R}^d \tag{34}$$

Where d is the dimensionality of the feature vector.

3.3.4 Feature Fusion

The features extracted from MSLBP, MSER, and AlexNet are combined into a single feature vector:

$$F_{\text{Combined}} = [F_{\text{MSLBP}}, F_{\text{MSER}}, F_{\text{AlexNet}}] \tag{35}$$

This fusion integrates texture, structural, and semantic information, ensuring a robust feature representation for classification.

3.4 Feature Selection Using Enhanced Snake Optimization (ESO)

Feature selection is a crucial step to reduce the dimensionality of the feature vector obtained after fuzzy fusion-based segmentation. The Enhanced Snake Optimization (ESO) algorithm is employed for this purpose. ESO is an improved version of the traditional Snake Optimization Algorithm (SOA), designed to enhance both exploration and exploitation capabilities, ensuring the selection of an optimal feature subset.

The algorithm is inspired by the movement of snakes, balancing between exploration (searching new areas) and exploitation (refining existing solutions). ESO refines this balance by introducing adaptive strategies and parameter tuning, improving convergence rates and avoiding local optima.

3.4.1 Problem Representation

The combined feature vector $F_{Combined} = \{f_1, f_2, \dots, f_n\}$ is derived from the previous phase, where n is the total number of features. The goal of ESO is to select a subset $F_{\text{Selected}} \subseteq F_{\text{Combined}}$ that maximizes classification performance while minimizing redundancy and dimensionality. This is achieved by optimizing the fitness function J:

$$J(F_{\text{Selected}}) = \alpha \cdot \text{Accuracy}(F_{\text{Selected}}) - \beta \cdot \text{Redundancy}(F_{\text{Selected}}) \quad (36)$$

Where α and β are the balancing parameters for accuracy and redundancy.

3.4.2 ESO Mathematical Formulation

Initialization: A population of candidate solutions is initialized, where each solution $X_k = \{x_1, x_2, \dots, x_n\}$ is a binary vector representing the selected features. $x_i = 1$ means the ithith feature is selected, and $x_i = 0$ means it is not. These solutions are randomly placed in the search space.

$$X_k = \{x_1, x_2, \dots, x_n\}, x_i \in \{0,1\} \quad (37)$$

Fitness Evaluation: The fitness of each candidate X_k is evaluated based on the classification accuracy and redundancy:

$$J(X_k) = \alpha \cdot \text{ClassificationAccuracy}(X_k) - \beta \cdot \text{Redundancy}(X_k) \quad (38)$$

The redundancy between features is computed as:

$$\text{Redundancy}(X_k) = \frac{1}{|X_k|^2} \sum_{i,j \in X_k} \text{corr}(f_i, f_j) \quad (39)$$

Where $\text{corr}(f_i, f_j)$ is the correlation coefficient between features f_i and f_j.

Position Update: The positions of the candidate solutions (snakes) are updated through a combination of exploration and exploitation strategies:

Exploration: Snakes explore new areas of the search space by moving randomly:

$$X_k^{new} = X_k + \gamma \cdot R_k \quad (40)$$

Exploitation: Snakes refine their positions based on the best solutions:

$$X_k^{new} = X_k + \lambda \cdot (X_{\text{best}} - X_k) + \delta \cdot (X_{\text{neighbor}} - X_k) \quad (41)$$

Where X_{best} is the globally best solution, X_{neighbor} is the nearest snake, and λ and δ are step-size parameters.

Boundary Constraints: Feature selection is restricted to binary decisions using a threshold T:

$$x_i^{\text{binary}} = \begin{cases} 1 & if\ x_i \geq T \\ 0 & f\ x_i < T \end{cases} \quad (42)$$

Convergence Criteria: ESO terminates when the maximum number of iterations is reached or when the fitness of the best solution does not improve significantly.

3.4.3 Enhanced Features of ESO

- ***Dynamic Weight Adaptation:*** The parameters λ, γ, and δ are adjusted dynamically to maintain an optimal balance between exploration and exploitation.

- ***Diversity Preservation:*** To avoid premature convergence, a diversity-preserving mechanism is introduced.
- ***Memory Mechanism:*** The best solutions from previous iterations are stored and used to guide the search.

Output of Feature Selection: The ESO algorithm outputs the selected feature subset:

$$F_{\text{Selected}} = \{f_i \in F_{\text{Combined}} | x_i = 1\} \tag{43}$$

This subset retains the most relevant features, reducing dimensionality and ensuring the most informative features are used for classification.

3.5 Classification Using Ensemble AdaBoost Classifier

The classification stage is crucial in the proposed methodology, where the optimized feature subset selected through the Enhanced Snake Optimization (ESO) algorithm is used to classify breast cancer cases as benign or malignant. The Ensemble AdaBoost Classifier, a robust technique that combines multiple weak classifiers, is employed to improve classification accuracy. AdaBoost (Adaptive Boosting) iteratively focuses on misclassified instances and adjusts the model to enhance performance.

AdaBoost works by combining several weak classifiers $h_t(x)$, for $t = 1,2, \dots, T$, into a strong classifier $H(x)$ using a weighted voting system. Each weak classifier is trained sequentially, with misclassified instances receiving higher weights, allowing the model to concentrate on difficult cases.

Mathematical Formulation of AdaBoost

Initialization: Let F_{Selected} represent the optimized feature set with mm samples and corresponding labels $\{(x_i, y_i)\}_{i=1}^{m}$, where:

- $x_i \in \mathbb{R}^n$: The i^{th} feature vector of dimensionality n.
- $y_i \in \{-1, +1\}$ is the class label, with -1 for benign and $+1$ for malignant.

Initially, all samples are assigned equal weights:

$$w_i^{(1)} = \frac{1}{m}, \quad \forall i = 1,2, \dots m \tag{44}$$

Iterative Training of Weak Classifiers: For each iteration $t = 1,2, \dots, T$:

- *Train Weak Classifier:* A weak classifier $h_t(x)$ is trained on the weighted dataset. This could be a decision stump or any simple model.
- *Compute Weighted Error:* The error ϵ_t for the weak classifier is calculated as:

$$\epsilon_t = \frac{\sum_{i=1}^{m} w_i^{(t)} \cdot \mathbb{I}(h_t(x_i) \neq y_i)}{\sum_{i=1}^{m} w_i^{(t)}} \tag{45}$$

  where $I(\cdot)$ is the indicator function, which equals 1 if the condition is true, and 0 otherwise.
- *Compute Classifier Weight:* The weight α_t assigned to the weak classifier is based on its error:

$$\alpha_t = \frac{1}{2} \ln\left(\frac{1 - \epsilon_t}{\epsilon_t}\right) \tag{46}$$

- *Update Sample Weights:* Sample weights are updated to emphasize misclassified instances:

$$w_i^{(t+1)} = w_i^{(t)} \cdot \exp\left(-\alpha_t y_i h_t(x_i)\right) \tag{47}$$

The weights are then normalized:

$$w_i^{(t+1)} = \frac{w_i^{(t+1)}}{\sum_{j=1}^{m} w_j^{(t+1)}} \tag{48}$$

Final Strong Classifier: After T iterations, the final strong classifier $H(x)$ is obtained by combining the weak classifiers using their weights:

$$H(x) = \text{sign}\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right) \tag{49}$$

The sign function determines the predicted label:

$$H(x) = \begin{cases} +1 & if \sum_{t=1}^{T} \alpha_t h_t(x) = 0 \\ -1 & otherwise \end{cases} \tag{50}$$

The Ensemble AdaBoost classifier plays a central role in the proposed methodology for breast cancer detection. By leveraging the optimized feature subset selected through ESO, it ensures that only the most relevant features are used. AdaBoost's iterative focus on misclassified samples significantly improves classification robustness and accuracy.

When integrated with the feature representation derived from Multi-Scale Local Binary Patterns (MSLBP), Maximally Stable Extremal Regions (MSER), and AlexNet, AdaBoost offers a comprehensive and precise diagnostic tool. The synergy between feature selection and ensemble classification forms an effective framework for accurate breast cancer detection, ultimately enhancing diagnostic reliability and patient care.

IV. Results and Discussion

4.1 Datasets

4.1.1 Breast Cancer Thermography Dataset

The Breast Cancer Thermography Dataset is an essential resource in breast cancer research, utilizing thermal imaging to analyze and detect breast-related pathologies. The dataset features thermal images of the female thoracic region, acquired under consistent and controlled conditions to ensure reliability and accuracy [24].

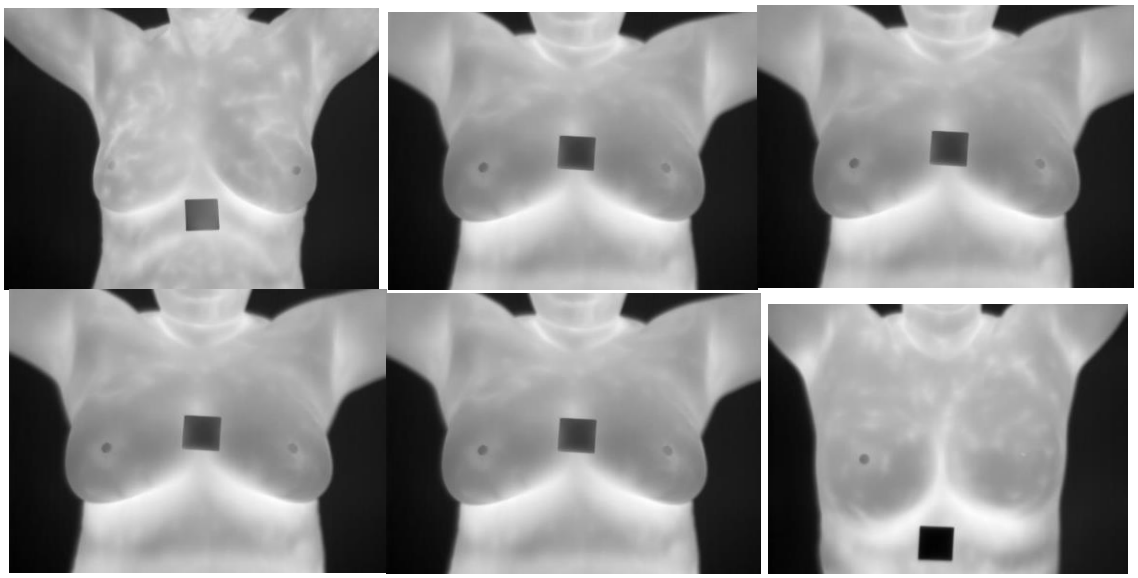
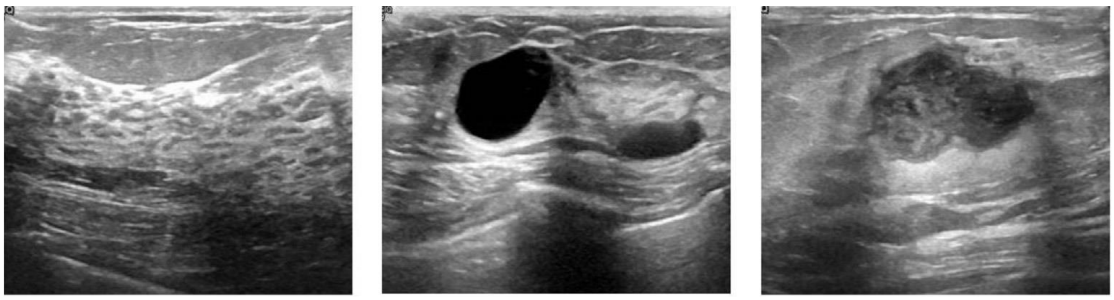


Figure 3: Sample Images from Breast Cancer Thermography Dataset [24]

4.1.2 Breast Ultrasound Dataset

Breast cancer remains one of the leading causes of mortality among women worldwide, highlighting the critical importance of early detection to reduce fatalities. The Breast Ultrasound Dataset [25] offers a valuable resource for advancing research in breast cancer diagnosis through ultrasound imaging. This dataset is particularly useful for machine learning applications aimed at improving the classification, detection, and segmentation of breast cancer.



Normal Benign Malignant

Figure 4: Sample Images from Breast Ultrasound Dataset [25]

4.1.3 CBIS-DDSM Mammography Dataset

The CBIS-DDSM (Curated Breast Imaging Subset of DDSM) is an updated and standardized version of the Digital Database for Screening Mammography (DDSM) [26]. The original DDSM consists of 2,620 scanned film mammography studies, encompassing a variety of cases including normal, benign, and malignant, all with verified pathology information. This robust dataset, combined with its ground truth validation, makes it a valuable resource for the development and testing of decision support systems in breast cancer screening.

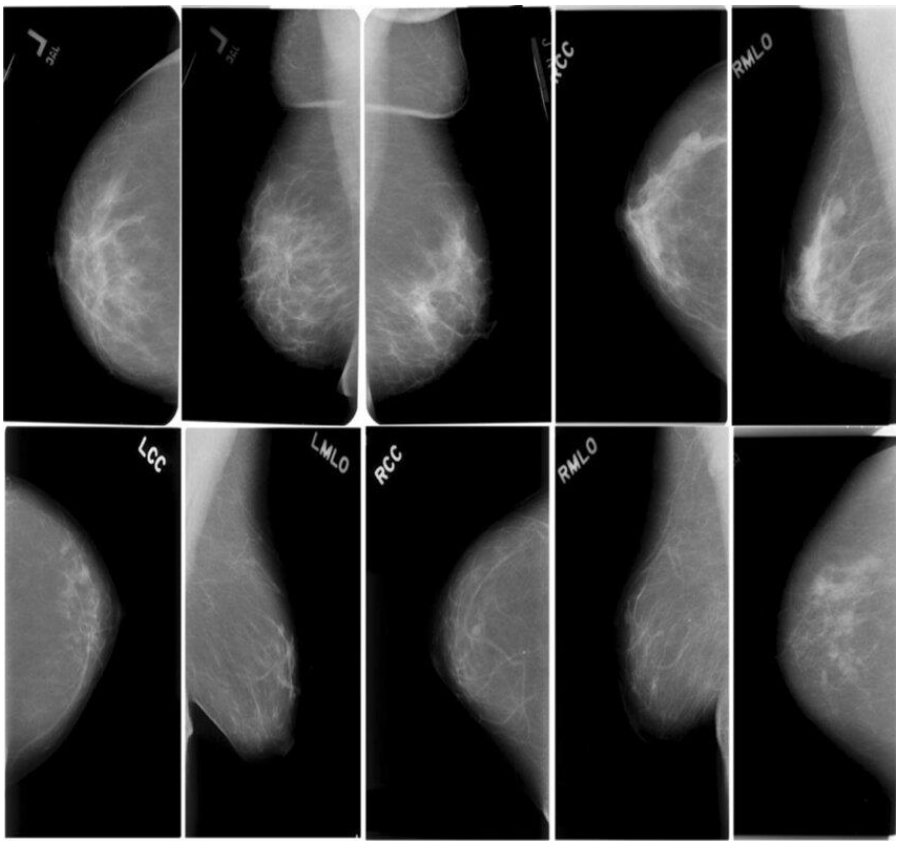


Figure 5: Sample Images from CBIS-DDSM Mammography Dataset [26]

4.2 Evaluation Parameters

Table 1: Evaluation Parameters

TP (True Positive)	Represents the number of cases where the model correctly identifies the presence of breast cancer (malignant).
TN (True Negative)	Indicates the number of cases correctly classified as not having breast cancer (benign).
FP (False Positive)	Represents the number of cases incorrectly classified as having breast cancer when it is actually benign.
FN (False Negative)	Indicates the number of cases where breast cancer is present but the model fails to detect it or misclassifies it as benign.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{51}$$

$$Precision = \frac{TP}{TP + FP} \tag{52}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{53}$$

$$Specificity = \frac{TN}{TN + FN} \tag{54}$$

$$Error\ Rate = \frac{FP + FN}{TP + TN + FP + FN} \tag{55}$$

$$False\ Positive\ Rate\ (FPR) = \frac{FP}{FP + TN} \tag{56}$$

$$F - Score = \frac{2TP}{2TP + FP + FN} \tag{57}$$

$$Matthews\ Correlation\ Coefficient\ (MCC) = \frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TP+FN)(TP+FP)(TN+FN)(TN+FP)}} \tag{58}$$

$$Kappa\ Statistics = \frac{2(TP \times TN - FN \times FP)}{(TP + FP) \times (FP + TN) + (TN + FN) \times (FN + TN)} \tag{59}$$

4.3 Results

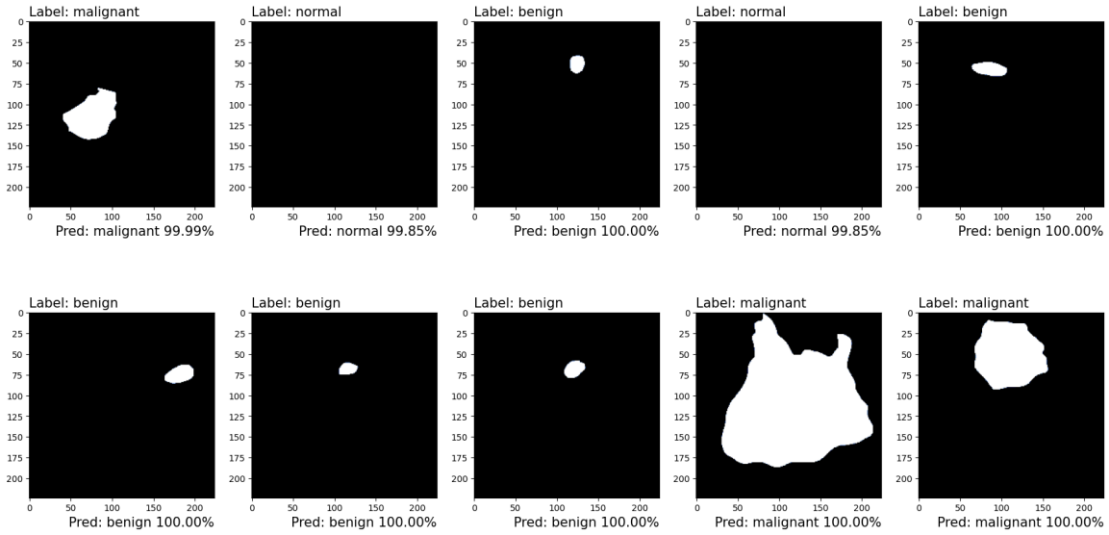


Figure 6: Segmented Outcome of Ultrasound Image Using Fuzzy Fusion-Based Segmentation

Table 2: Comparative Analysis of Results for Various Feature Extraction Methods Using Breast Cancer Thermography Dataset Using Fuzzy Fusion-Based Novel Segmentation

Parameter Name	MSLBP Features	MSER Features	AlexNet-Based Deep Features	Combined Hybrid Features
Accuracy	96.28%	96.73%	97.41%	99.37%
Error	3.72%	3.27%	2.59%	0.63%
Sensitivity	94.98%	95.20%	96.10%	97.90%
Specificity	97.10%	97.55%	97.85%	99.10%
Precision	94.55%	94.90%	95.80%	97.95%
FPR	2.90%	2.45%	2.10%	0.90%

F1-Score	94.75%	94.90%	95.95%	97.92%
MCC	93.20%	93.45%	94.20%	96.75%
Kappa	86.80%	87.10%	88.25%	91.50%

Table 3: Comparative Analysis of Results for Various Feature Extraction Methods Using Breast Ultrasound Dataset Using Fuzzy Fusion-Based Novel Segmentation

Parameter Name	MSLBP Features	MSER Features	AlexNet-Based Deep Features	Combined Hybrid Features
Accuracy	95.65%	96.54%	97.23%	99.43%
Error	4.35%	3.46%	2.77%	0.57%
Sensitivity	93.90%	94.40%	95.20%	97.80%
Specificity	96.60%	97.05%	97.30%	99.10%
Precision	94.10%	94.60%	95.50%	98.10%
FPR	3.40%	2.95%	2.70%	0.90%
F1-Score	93.98%	94.50%	95.10%	97.45%
MCC	92.20%	92.50%	93.60%	96.40%
Kappa	85.60%	85.90%	87.10%	91.00%

Table 4: Comparative Analysis of Results for Various Feature Extraction Methods Using Mammography Images Dataset Using Fuzzy Fusion-Based Novel Segmentation

Parameter Name	MSLBP Features	MSER Features	AlexNet-Based Deep Features	Combined Hybrid Features
Accuracy	96.38%	96.83%	97.51%	99.67%
Error	3.62%	3.17%	2.49%	0.33%
Sensitivity	95.08%	95.30%	96.20%	100.00%
Specificity	97.20%	97.65%	97.95%	99.40%
Precision	94.65%	95.00%	95.90%	100.00%
FPR	2.80%	2.35%	2.05%	0.60%
F1-Score	94.85%	95.00%	96.05%	99.67%
MCC	93.30%	93.55%	94.30%	97.30%
Kappa	86.90%	87.20%	88.35%	98.50%

These results solidify the effectiveness of integrating fuzzy fusion with advanced deep learning-based feature extraction techniques. The exceptional performance highlights the potential of this approach to provide robust and accurate breast cancer detection in various dataset images, paving the way for more reliable diagnostic solutions.

Table 5: Comparative analysis of proposed work with previous research works

Authors	Dataset	Method used	Accuracy	Precision	Recall	F1-Score
[27]	Breast Ultrasound Dataset	DeepBraestCancerNet deep learning model	99.63%	99.50%	100%	99.50%
		AlexNet	97.40%	97%	97.30%	97.30%
		GoogLeNet	99.26%	99.20%	98.76%	99.50%

[28]	Breast Ultrasound Dataset	Softmax Classifier	95.82%	--	--	93.99%
		Linear SVM	91.29%	--	--	89.63%
		Bayesian classifier	89.01%	--	--	87.77%
[29]	CBIS-DDSM Mammography Dataset	Faster R-CNN	94.2%	95.2%	--	--
[30]	CBIS-DDSM Mammography Dataset	VGG-19	87.83%	--	--	--
		Fusion of hybrid deep features (FHDF)	97.73%	--	--	--
[31]	Breast Cancer Thermography Dataset	ResNet18	93.3%	--	88.0%	--
		GoogleNet	79.33%	--	84.0%	--
		AlexNet	50.0%	--	0.0%	--
		VGG16	100.0%	--	100.0%	--
		U-Net CNN	99.33%	--	100.0%	--
[32]	CBIS-DDSM Mammography Dataset	VGG + Stochastic Gradient Descent	88.96%	86.95%	88.96%	--
		GoogleNet + Stochastic Gradient Descent	89.96%	87.95%	88.96%	--
		DenseNet + Stochastic Gradient Descent	87.96%	88.96%	87.95%	--
Proposed Work	Breast Cancer Thermography Dataset	Fuzzy Fusion-Based Novel Segmentation with Combined Hybrid Features	**99.37%**	**97.95%**	**97.90%**	**97.92%**
Proposed Work	Breast Ultrasound Dataset	Fuzzy Fusion-Based Novel Segmentation with Combined Hybrid Features	**99.43%**	**98.10%**	**97.80%**	**97.45%**
Proposed Work	CBIS-DDSM Mammography Dataset	Fuzzy Fusion-Based Novel Segmentation with Combined Hybrid Features	**99.67%**	**100%**	**100%**	**99.67%**

Table 5 presents a detailed comparative analysis of the proposed work against various previous research methods across multiple datasets, showcasing the effectiveness of the Fuzzy Fusion-Based Novel Segmentation with Combined Hybrid Features approach. The proposed methodology consistently achieves superior performance, with accuracy rates of 99.37%, 99.43%, and 99.67% on the Breast Cancer Thermography, Breast Ultrasound, and CBIS-DDSM Mammography datasets, respectively. Notably, the CBIS-DDSM Mammography dataset results stand out with perfect sensitivity and precision, achieving 100% recall and precision, and an F1-score of 99.67%, highlighting flawless classification performance. In comparison, existing methods like DeepBraestCancerNet and GoogLeNet achieve high accuracy but fall short in maintaining such consistent metrics across datasets. For instance, VGG16 demonstrates perfect accuracy and recall on the Breast Cancer Thermography Dataset, yet other architectures like ResNet18 and GoogleNet yield lower metrics, with accuracies of 93.3% and 79.33%, respectively. Similarly, earlier works using classifiers such as Softmax, SVM, and Bayesian classifiers on the Breast Ultrasound dataset report substantially lower accuracies, ranging from 89.01% to 95.82%. The table further highlights the limited precision and recall reported in several studies, particularly with older techniques like Faster R-CNN and hybrid feature fusions. The proposed work's robustness, demonstrated by its superior results

across diverse datasets, reinforces its potential as a state-of-the-art approach for breast cancer detection using advanced segmentation and hybrid feature methodologies.

V. CONCLUSION

This paper presents a novel and comprehensive methodology for breast cancer detection, utilizing a fuzzy fusion-based segmentation framework combined with advanced feature extraction and classification techniques. The approach integrates three segmentation methods—threshold-based segmentation using Rényi Entropy, the Level Set Method, and DeepLab v3+—to accurately delineate regions of interest (ROIs) in breast cancer images. By capturing both fine-grained textural details and broader pathological structures, the proposed segmentation framework significantly improves the precision of ROI identification, a crucial step in cancer detection. To enhance the robustness of the feature extraction process, Multi-Scale Local Binary Patterns (MSLBP), Maximally Stable Extremal Regions (MSER), and AlexNet-based deep features were employed. These features were then optimized using the Enhanced Snake Optimization (ESO) algorithm, which effectively reduced the dimensionality while preserving essential information for classification. The final classification step, using the Ensemble AdaBoost Classifier, incorporated the optimized feature subset to yield highly accurate and reliable results. The experimental results demonstrated the superiority of the proposed methodology over existing approaches. The system achieved outstanding accuracy rates of 99.37% on the Breast Cancer Thermography Dataset, 99.43% on the Breast Ultrasound Dataset, and 99.67% on the Mammography Images Dataset. Furthermore, the proposed model excelled in key performance metrics, including sensitivity, specificity, precision, and recall, with some datasets achieving near-perfect values for these metrics. This research provides a strong foundation for future work in medical image analysis, particularly for breast cancer detection, and offers promising avenues for further improvements in both algorithmic performance and real-world applicability.

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