Multiresolution Texture Driven Breast Cancer Detection Using a Modified Particle Swarm Optimization Method

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***Abstract*—The diagnosis of breast cancer heavily depends on feature selection methods to extract important traits from tissue samples or medical imaging. This paper presents a feature selection method uses Modified Particle Swarm Optimization (MPSO). Based on the best features, breast tissue is classified as benign or malignant using SVM, MLP, and RF after three feature extraction techniques—HLG, GLRLM, and WPT1F—are applied. In terms of accuracy, sensitivity, and specificity, MPSO outperformed conventional techniques in training and evaluation using craniocaudal (CC) view images from the DDSM dataset. Because of its compactness and informativeness, the MPSO feature subset is known to improve early breast cancer detection. The model's generalization across a variety of imaging modalities was supported by validation of its performance on additional datasets from different mammographic views. Greater correlation between the expected and actual results, as well as reduced type-I and type-II errors to produce more accurate predictions, are indicated by a higher kappa value.**

***Keywords*— Particle swarm optimization, Mammographic images, Computer aided detection, Wavelet packet transform, LBP, GLCM, GLRLM**

I. INTRODUCTION

At 11.6% of all cancer cases, breast cancer is currently the second most common cancer in women worldwide. At 6.9% of all cancer deaths, it is also the primary cause of cancer-related deaths in women. This cancer's worldwide impact is demonstrated by the fact that it is the most diagnosed cancer in 157 out of 185 countries [1].

Based on their growth pattern and potential for metastasis, tumors—abnormal cell growths—are categorized as either benign or malignant in oncology [2]. Benign tumors grow slowly without affecting neighbouring tissues, are non-cancerous, and typically remain in one location. Depending on their size and location, they can cause issues even though they are typically not life-threatening. On the other hand, malignant tumors are cancerous by nature. Their unique characteristics are highlighted by their quick spread, increased mortality risk, and need for more forceful interventions [3]. Accurate diagnosis and the development of a treatment plan depend on this classification. Conventional methods of diagnosing breast cancer, including clinical evaluations, self-examinations, ultrasound imaging, mammography, and biopsies [4], are often limited and prone to human error. However, the advent of machine learning (ML) has significantly changed the medical field by improving diagnosis accuracy and effectiveness [5].

By analyzing medical images, computer-aided detection (CAD) technologies help reduce human error, increase the chances of survival, and assist radiologists in detecting breast cancer early [6]. By identifying the most important data features, feature selection—a crucial part of machine learning pipelines—improves model performance. Focusing on relevant features can increase the accuracy and robustness of the model while also increasing computational efficiency.

The structure of this paper is as follows: A review of relevant feature selection literature is presented in Section 2, with a focus on general hybrid approaches, Particle Swarm Optimization (PSO), and the Firefly Algorithm (FA). The suggested method modified Particle Swarm Optimization (MPSO), is described in detail in Section 3. Section 4 presents the experimental setup and results, and Section 5 presents the conclusions and future research directions.

II. RELATED WORKS

Nature-inspired metaheuristic algorithms are becoming more common in many fields to solve complex optimization problems. Examples include the grey wolf optimization algorithm [7], artificial bee colony algorithm [8], whale optimization algorithm [9], cuckoo search algorithm [10], lion optimization algorithm [11], crow search algorithm [12], dragonfly algorithm [13], and salp swarm algorithm [14]. Particle swarm optimization (PSO), a widely used bio-inspired optimization method, is often used for feature selection. For example, Sam Bose and his team [15] used convolutional neural networks (CNNs) to extract features from medical images. They then used advanced optimization methods like PSO and genetic bee colony (GBC) to find the most important features. These selected features were then used with machine learning classifiers, such as support vector machines (SVM), linear discriminant analysis (LDA), k-nearest neighbors (KNN), and random forest (RF).

Among these, the multiclass classification accuracy of 98.21% was attained by the GBC and RF combined model, indicating a significant improvement in accuracy, specificity, sensitivity, PPV, and NPV.
In a similar vein, Mohamed Abd Elaziz et al. [16] introduced a cutting-edge feature selection model for medical imaging that uses fractional order modified heterogeneous comprehensive learning particle swarm optimization (FMHCLPSO) to improve performance. Their internet of medical things (IoMT) model outperformed other frameworks in datasets like COVID-19 and pneumonia X-rays by combining this technique with a multilevel thresholding approach to image segmentation and feature extraction. With their political system-based sine cosine optimization (PSCSO) algorithm, which incorporates a novel position-updating mechanism, Kiani et al. [17] made yet another noteworthy contribution to optimization. This model did well in engineering applications, benchmark functions, and global optimization. By creating a social cognitive swarm optimization (SCSO) technique for feature selection, Ali Hameed et al. [18] also made important contributions. SCSO has been demonstrated to perform better than traditional techniques like PSO and grey wolf optimization in hyperspectral datasets. Additionally, by adding randomness to a method called crazy particle swarm optimization (CPSO), Behera et al. [19] increased the global search efficiency. Using the INBreast dataset, Manimurugan et al. [20] created a thorough CAD system for breast cancer detection. They used VGG-19 for feature extraction, Res-SegNet for segmentation, and mCLAHE-based preprocessing in their pipeline. The classification stage demonstrated the enormous potential of hybrid approaches in medical diagnostics by achieving an accuracy of over 98% using an optimized PSO with a stacked autoencoder. The study shows that high accuracy can be attained by combining techniques like CNN, GBC, and CAD models. With improved optimization, more sophisticated versions like FMHCLPSO, CPSO, and SCSO were shown to perform better in medical imaging, segmentation, and classification tasks.

The firefly algorithm is a sophisticated bioinspired metaheuristic algorithm that has been used in a number of applications, including classification, feature selection, optimization, and image segmentation. To get around the algorithm's drawbacks, researchers have put forth a number of creative changes. For instance, Bacanin et al. [21] established a GOQRFA model with greater exploration and exploitation by combining quasi reflection learning with uniform crossover and Gaussian mutation. In order to improve classification accuracy with classifiers such as C4.5 and Bayesian networks, Selvakumar et al. [22] used filter and wrapper techniques based on mutual information and FA. In addition to these, Xie et al. [23] used an enhanced version of mRMR with multilayer binary FA (MBFA) to improve performance in order to address the issue of the two-phase method for dimensionality reduction.

CoFA, created by Peng et al. [24], is another advancement. By drawing fireflies to both random and elite peers who did well in breast cancer datasets, this method dynamically diversifies populations. Al-Thanoon et al. [25] iteratively increased classification accuracy by using FA to adjust PSVM parameters. M et al. [26] employed hybrid FA techniques to improve performance and imputation approaches to produce balanced datasets. By enhancing feature extraction layers, Vijendran et al. [27] classified different types of brain tumors using the adaptive FA and CNNs (AFFOCNN) model.

Improvements also addressed particular issues: Sharma et al. [29] used Tsallis entropy with FA for accurate image segmentation, and Wang et al. [28] suggested NaFA, a neighborhood restricted FA variant that improves convergence. For multilevel thresholding of color images, Pare et al. [30] created a modified fuzzy entropy-based FA that demonstrated increases in segmentation efficiency and fidelity. To balance transparency and robustness in watermarking, Moeinaddini [31] used discrete FA, and Kazemivash et al. [32] used FA to optimize regression tree-based watermarking. With its versatility and optimization skills, FA continues to push boundaries, transforming fields from hybrid models for EEG emotion recognition to entropy-infused clustering mechanisms.

The insights show how FA can handle a range of optimization issues.

Researchers have created a number of hybrid optimization models in recent years that not only solve the problem but also achieve faster convergence and better performance. The butterfly optimization algorithm (BOA) and the ant lion optimizer (ALO) were combined to create BOAALO by Thawkar, S. et al. [33]. By choosing an ideal subset of mammogram features to be used in classifying breast tissue as benign or malignant using classifiers such as ANN, adaptive neuro-fuzzy inference system (ANFIS), and SVM, the study seeks to increase the accuracy of breast cancer diagnosis. A hybrid ML-MDKL feature subset selection and classification method was presented by Rekha, K. S. et al. [34]. It is improved by a levy flight-based cuckoo search optimization algorithm (H-RS-LVCSO) and a rat swarm optimizer (RSO). The method aims to improve the algorithm's local search capabilities and optimization speed. When dealing with big, high-dimensional data sets, it focuses on the challenge of selecting the most pertinent features. A hybrid algorithm called CSAHHO, which combines the crow search algorithm (CSA) and Harris Hawks optimization (HHO) for feature selection and mass classification in digital mammograms to diagnose breast cancer, was proposed by Thawkar, S. et al. [35]. By employing the suggested CSAHHO algorithm to identify the most pertinent features from mammograms, the study seeks to increase the precision of breast cancer diagnosis. The ANN and SVM classifiers are then used to classify the masses as benign or malignant based on the chosen features. 651 mammogram images from the DDSM dataset are used to test the suggested algorithm's performance.

The proposed study MPSO effectively explores the solution space by modifying particle positions according to their own best-known positions and the best positions of their neighbors,

III. DATA AND METHODOLOGY

A total of 974 pictures, including both benign and malignant ones, were selected from the DDSM dataset [36]. It includes 424 malignant and 550 benign images, all of which show the craniocaudal (CC) view.

The suggested architecture, which is separated into four main stages, is shown in Fig. 1. Image preprocessing is completed in the first stage. Activities related to feature extraction are carried out in the second phase. To find the most pertinent features, a modified particle swarm optimization (MPSO) feature selection methodology is used in the third phase. The fourth step employs SVM, MLP, and RF classifiers to categorize breast tissue as benign or malignant using the chosen features.

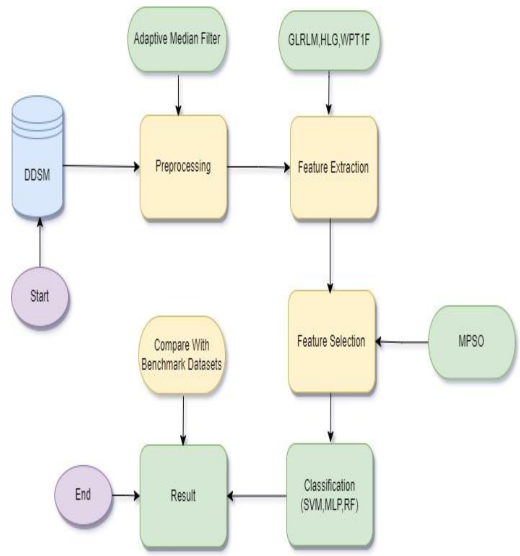

Fig. 1. Proposed architecture

A. Preprocessing

Impulsive noise was eliminated from mammography images using an adaptive median filtering algorithm while preserving key features and enhancing overall image quality.

B. Extraction of features.

Three distinct feature extraction techniques were applied: HLG, GLRLM, and WPT1F. These techniques were all intended to capture different facets of texture information in an image.

1. HLG (Hybrid LBP-GLCM)

Figure 2 outlines the proposed Hybrid Local Binary Pattern–Gray Level Co-occurrence Matrix (HLG) framework for multiresolution texture characterization of mammographic images, essential for breast cancer detection [37]. The workflow begins with converting color mammograms to grayscale, reducing computational load while retaining structural details. Local Binary Pattern (LBP) features are then extracted, providing detailed local texture information through neighborhood comparisons around each pixel [38]. Following this, Gray Level Co-occurrence Matrix (GLCM) analysis is conducted on the LBP image to model higher-order spatial relationships, extracting statistical descriptors like contrast and correlation. These LBP and GLCM features are flattened and merged into a unified feature vector, enhancing class separability between benign and malignant cases for classification processes using machine learning or deep learning models. The HLG framework effectively utilizes both local and global texture characteristics for improved detection accuracy.

This method combines six texture descriptors over two-pixel distances and four angular directions to produce a 48-dimensional feature vector [38].

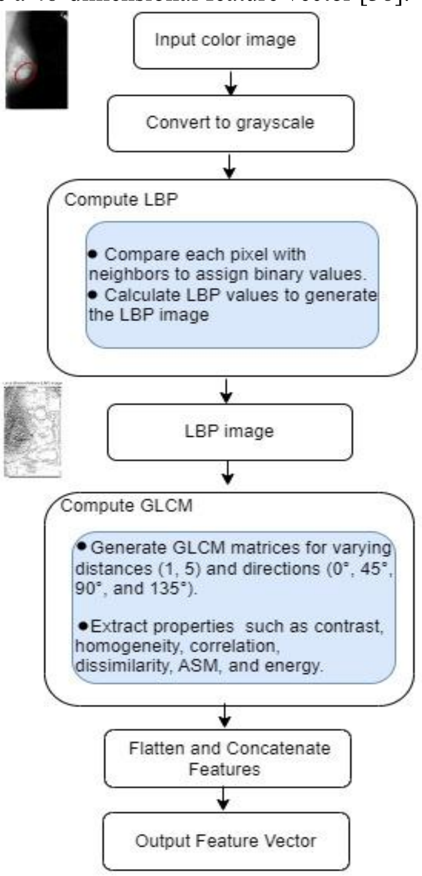

Fig. 2. Flowchart for HLG Feature Extraction

2. GLRLM (Gray-Level Run-Length Matrix)

A statistical texture descriptor called GLRLM [39] characterizes the distribution of grey-level runs in images, where a run consists of consecutive pixels with the same grey-level value. Key features include Short Run Emphasis (SRE), Long Run Emphasis (LRE), Gray-Level Non-Uniformity (GLN), and others, calculated at angles of 0°, 45°, 90°, and 135°. This approach generates a 40-dimensional feature vector, capturing both fine and coarse textures of the image [40].

3. WPT1F (WPT-First order)

Wavelet Packet Transform–based First-Order Feature (WPT1F) extraction framework, designed for extracting multiresolution frequency-domain attributes from mammographic images. The process starts with wavelet packet decomposition of the input image to two levels, producing sub-bands for various frequency orientations: approximate, horizontal, vertical, and diagonal [41]. This decomposition offers a more detailed frequency partitioning than conventional discrete wavelet transforms, preserving important textural distinctions of breast tissue. At each level, the approximate sub-band receives further decomposition to enhance low-frequency structural element representation, while directional sub-bands retain high-frequency edge and texture data. Five first-order statistical features (mean, variance, skewness, kurtosis, and energy) are derived from the selected sub-bands to characterize intensity distribution and texture complexity across frequency bands. These features effectively summarize statistical characteristics of coarse and fine textures observable in mammograms. Finally, extracted features from the sub-bands are aggregated into a cohesive feature vector, providing a comprehensive multiscale representation of mammographic textures. The WPT1F feature vector is utilized for feature selection and classification, improving differentiation between benign and malignant breast lesions [42].

GLRLM contained 40 features, whereas 48 features were computed for HLG. Finally, WPT1F had ten features. Total 98 features were produced by combining these features.

C. Modified Particle Swarm Optimization (MPSO) for Feature Selection

Modified Particle Swarm Optimization (MPSO) simulates the collective behavior of organisms like fish and birds to efficiently explore complex problem domains for optimal feature selection. Each particle represents a potential solution with a velocity that dictates its movement [43]. By balancing exploration of new areas and exploitation of known solutions, PSO iteratively adjusts particle positions based on individual and global best solutions. Key factors influencing particle movement include inertia weight (momentum), cognitive component (personal best), and social component (swarm best).

Updating of velocity is done by following equation,

$$V_i^{(t+1)} = w * V_i^{(t)} + c_1 * r_1 * \sin(P_{pos,i} - X_i^{(t)}) + c_2 * r_2 * \sin(G_{pos} - X_i^{(t)}) \quad (1)$$

Where:

- w is the inertia weight that moderates the contribution of the prior velocity,
- c_1 and c_2 are cognitive and social learning coefficients, respectively,
- r_1 and r_2 are random numbers ranging from [0,1],
- $P_{pos,i}$ is personal best position of i^{th} particle,
- G_{pos} is the overall best position the swarm has obtained,
- $X_i^{(t)}$ is the present position of the of i^{th} particle,
- $V_i^{(t)}$is the velocity of the i^{th} particle at iteration t.

The position of every particle is then updated through:

$$X_i^{(t+1)} = X_i^{(t)} + V_i^{(t+1)} \quad (2)$$

Algorithm1: Pseudo code of Modified Particle Swarm Optimization (PSO)

There are following steps in this algorithm.

Step 1. Initialize Parameters:

- Set the feature dimensions (D) to 98, the number of particles (n) to 10, and the number of iterations (T) to 100.
- w=0.5, c1 =1.5, c2=1.5

Step 2. Particle Initialization:

For every particle *i* (*i* =1 to *n*):

- for *D* features initialize position X_i at random in range [0, 1].
- for *D* features initialize velocity V_i at random in range [-1, 1].

Step 3. Initialize personal best:

- Establish your own best position $P_{pos,i} = X_i$.
- Take the negative of the model's classification accuracy to find the particle's fitness at position X_i.
- $P_{fitness,I}$ is the stored value

Step 4. Identify the Global Best:

- Calculate $G_{pos,}$ as the location with the minimum fitness for a paricle,
- Calculate fitness value as $G_{fitness}$ for the position of this particle

Step 5. Iterative Optimization:

a) For each particle *i*:

i.Produce random values:

- Produce vector values r_1 and $r_{2,}$ of size *D* each.in uniform range (0,1)

ii.Use Eq (1) to update the velocity

iii.Use Eq (2) to update the position.

iv.Apply feature threshold:

If ($X_{i,j}$ > 0.5) choose feature j; else reject it.

v.Calculate fitness:

- Assess the fitness of this position X_i on this selected feature.

vi.Update Personnel Best:

- If the fitness of $X_i > P_{fitness,i}$
  - $P_{pos,i} = X_i$
  - e $P_{fitness,i}$ = fitness of X_i

b) Update Global Best:

- Find G_{pos} as the particle with the least fitness,
- Find $G_{fitness}$ for this position.

Step 6. Repeat iterations:

- For T iterations, repeat steps 5.

Step 7. Output:

- Return the optimum global location Gpos
- Return fitness Gfitness for this position.

IV. RESULT AND DISCUSSION

A. Performance Comparison of Classifiers with Feature Selection

Table 1 presents the classification results for Random Forest (RF), Multilayer Perceptron (MLP), and Support Vector Machine (SVM) classifiers applied to the DDSM dataset, contrasting performance with and without the proposed MPSO based feature selection method. While all classifiers demonstrate acceptable performance when utilizing the complete feature set, the integration of MPSO consistently yields substantial enhancements across all evaluation metrics [44]. Specifically, for the Random Forest classifier, the proposed approach elevates accuracy from 87.24% to 94.91%, accompanied by corresponding improvements in precision (from 89.27% to 96.10%), recall (from 85.82% to 91.58%), and specificity (from 92.93% to 97.46%).

Likewise, the MLP classifier demonstrates enhanced performance through optimized feature selection, attaining an accuracy of 96.81% as opposed to 93.92% without it, alongside a high precision of

97.83% and an improved specificity of 99.19%. The most significant enhancement is evident in the SVM classifier, where MPSO increases accuracy from 94.95% to 98.97%, achieving perfect sensitivity (TPR = 100%) and a specificity of 97.28%. These findings unequivocally illustrate that the proposed MPSO framework effectively removes redundant and non-informative features, thus improving class separability and bolstering diagnostic reliability across various classifiers within the DDSM dataset.

Table 1: Classification results of MPSO over DDSM dataset.

Classifier	FS method	Accuracy %	Precision %	Recall % TPR	Specificity% TNR
Random Forest	No method (all features)	87.24	89.27	85.82	92.93
	MPSO	94.91	96.10	91.58	97.46
MLP	No method (all features)	93.92	95.84	92.86	97.46
	MPSO	96.81	97.83	92.86	99.19
SVM	No method (all features)	94.95	92.85	95.22	94.74
	MPSO	98.97	98.80	100.00	97.28

Table 2 provides a comparative assessment of Type I error [45], Type II error [46], and Cohen's Kappa coefficient [47] across various classifiers utilizing the proposed MPSO-based feature selection methodology. The Random Forest classifier displays comparatively elevated misclassification rates, characterized by a Type I error of 4.65% and a Type II error of 11.86%, which corresponds to a considerable degree of agreement (κ = 0.853). Conversely, the Multilayer Perceptron (MLP) classifier exhibits enhanced dependability, as evidenced by a reduction in both Type I and Type II errors to 2.83% and 8.34%, respectively, and a superior agreement score (κ = 0.905). The Support Vector Machine (SVM) classifier demonstrated superior performance, achieving the lowest error rates: a Type I error of 1.82% and a Type II error of 1.38%, while also exhibiting near-perfect concordance with the ground truth labels (κ = 0.985). These results substantiate the efficacy of the proposed MPSO-based feature selection framework [48] in improving diagnostic consistency and reducing both false positive and false negative predictions; consequently, the SVM classifier proved to be the most dependable for breast cancer detection.

Table 2: Comparison of Classification Errors ..

Classifier	FS method	Type 1	Type 2	Kappa Coefficient
Random Forest	MPSO	4.65	11.86	0.853
MLP	MPSO	2.83	8.34	0.905
SVM	MPSO	1.82	1.38	0.985

B. Comparison of MPSO with Advanced State-of-the-Art Methods

Table 3 compares the classification accuracy achieved by different feature selection algorithms across three benchmark mammographic datasets, namely DDSM (MLO view) [36], INBREAST [49], and MIAS [50]. On the DDSM dataset, the proposed MPSO method outperforms conventional metaheuristic approaches, achieving the highest accuracy of 96.90%, surpassing Firefly Algorithm (95.46%), Ant Lion Optimizer (94.43%), Butterfly Optimization Algorithm (93.41%), and Genetic Algorithm (93.41%). A similar trend is observed on the INBREAST dataset, where MPSO attains a competitive accuracy of 91.28%, closely matching the performance of FA (91.36%) and outperforming ALO, BOA, and GA. On the MIAS dataset, MPSO again demonstrates superior robustness by achieving an accuracy of 90.25%, outperforming BOA and GA and yielding performance comparable to ALO (90.33%).

These results indicate that the proposed MPSO-based feature selection approach exhibits strong generalization capability across diverse mammographic datasets with varying imaging characteristics, consistently providing higher or comparable accuracy than existing optimization techniques.

Table 3: Performance of Feature Selection Methods on Various Datasets

Dataset	Algorithm	Accuracy
DDSM (MLO)	FA	95.46
	ALO	94.43
	BOA	93.41
	GA	93.41
	MPSO	96.90
INBREAST	FA	91.36
	ALO	88.27
	BOA	88.79
	GA	88.27
	MPSO	91.28
MIAS	FA	88.79
	ALO	90.33
	BOA	87.76
	GA	87.25
	MPSO	90.25

V. CONCLUSION AND FUTURE DIRECTIONS

There are a lot of different ways to diagnose breast cancer, but researchers still have a hard time figuring out the best way to create a trustworthy diagnostic system. We presented a MPSO method in this paper. Three classifiers—SVM, MLP, and RF—were used to predict whether breast tissue is benign or malignant based on a subset of features from the suggested method. Three benchmark datasets were used to evaluate the efficacy of the suggested hybrid technique. On the DDSM and benchmark datasets, the MPSO approach performed better than current feature selection methods, achieving higher prediction accuracy and better convergence.

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