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# Enhanced Breast Cancer Detection Using Modified Particle Swarm Optimization-Based Back Propagation Neural Network

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## ABSTRACT

Breast cancer detection faces challenges due to late diagnosis and inaccurate results, leading to improper treatment. Particle Swarm Optimization (PSO), a common optimization technique, often gets trapped in local optima, resulting in high false negatives and computational time. To address this, a study devised a modified PSO-based Back Propagation Neural Network (BPNN) using White Shark Optimization (WSO) for more accurate breast cancer detection. The research collected 1097 mammogram images from two medical centers and categorized them into benign, and malignant groups. Image preprocessing involved techniques like Otsu's method and contrast limited adaptive histogram equalization, with Fuzzy C Means used for segmentation. Region of Interest (ROI) extraction utilized Gabor filter and Local Binary Pattern, followed by weighted average fusion of textural features. WSPSO was then applied for optimal feature selection, and BPNN classified the identified features. MATLAB R2016a implemented the system. Evaluation metrics included accuracy, precision, sensitivity, specificity, False Positive Rate (FPR), and Computation Time (CT). Compared to PSO-BPNN, WSPSO-BPNN demonstrated superior performance. The accuracy, precision, sensitivity, specificity, FPR and CT of WSPSO-BPNN for malignant dataset were 96.88%, 99.08%, 96.43%, 97.92%, 2.08%, and 32.38 seconds, respectively, while the corresponding values for PSO-BPNN were 93.13%, 96.33%, 93.75%, 91.67%, 8.33% and 44.03 seconds, respectively. Also for the accuracy, precision, sensitivity, specificity, FPR and CT of WSPSO-BPNN for benign dataset were 96.15%, 98.14%, 96.34%, 95.71%, 4.29%, and 40.04 seconds, respectively, while the corresponding values for PSO-BPNN were 93.59%, 96.27%, 94.51%, 91.43%, 8.57% and 61.94 seconds respectively showcasing its potential for improving breast cancer diagnosis.

**Keywords**: Back Propagation Neural Network, Breast Cancer, Classification, Mammogram Images, Particle Swarm Optimization, White Shark Optimization.

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## 1. INTRODUCTION

Breast cancer represents a formidable global health challenge with diverse incidence and mortality rates [8]. Detecting cancer early is crucial, and mammography stands as a key diagnostic tool despite its susceptibility to false positives and negatives. Complicating factors such as breast density and patient demographics further hinder precise diagnosis. Against this backdrop, novel approaches that integrate imaging techniques and signal processing methods, including the exploration of optimization algorithms like Particle Swarm Optimization (PSO), are gaining traction in breast cancer classification. The urgency of addressing breast cancer as a global concern underscores the necessity for advanced diagnostic methods. Machine learning, particularly Neural Networks, holds significant position in this realm.

However, obstacles such as local minima, slow convergence, and overfitting have hampered the effectiveness of techniques like Back Propagation Neural Networks (BPNN) [7]. While some studies have made strides in addressing specific challenges, a comprehensive solution remains elusive. Hence, this research endeavors to develop a tailored approach, the modified PSO-BPNN, to confront these obstacles in breast cancer classification. This research's principal objective is to craft a modified PSO-BPNN framework for accurately classifying breast cancer in mammograms. To fulfill this objective, specific tasks include devising the classifier technique, formulating the White Shark-PSO algorithm, implementing BPNN with WSPSO, simulating the technique using MATLAB, and conducting a comprehensive evaluation based on various performance metrics. By introducing a novel fusion of swarm intelligence and neural networks, this research aims to enhance the precision of breast cancer classification. Such advancements hold promise for reshaping existing computer-aided diagnostic systems, reducing dependence on manual interpretation, and enhancing early detection rates.

Ultimately, these developments could lead to earlier interventions and improved healthcare outcomes for individuals at risk of breast cancer. The research's scope encompasses several stages of image analysis, from acquisition to preprocessing, segmentation, feature extraction, and feature selection, leveraging PSO and WSPSO. Additionally, it introduces a novel method for combining extracted features and employs WSPSO-BPNN for image classification, contributing to the evolving landscape of breast cancer diagnosis. Breast cancer, constituting a significant portion of cancer cases [1], often requires early detection facilitated by imaging techniques like mammography. Despite its importance, distinguishing abnormalities in breast tissue structure can be challenging. Traditional methods involve manual biopsies or Computer-Aided Diagnosis (CAD) systems to differentiate between normal and cancerous images, aiming to minimize false-negative and false-positive rates [3].

Mammography, utilizing X-ray images, remains a cornerstone in breast cancer detection, though subtle visual cues in early stages complicate diagnosis. Automated methods integrating Neural Networks and Fuzzy Logic aid in detecting, segmenting, and classifying masses from mammograms, employing feature extraction and texture analysis for image classification. Modern mammography techniques, evolving from early practices, prioritize improved image quality and reduced radiation exposure for safer screening. Current techniques expose the breast to lower levels of radiation, emphasizing advancements in minimizing radiation exposure for safer screening [2]. Figure 1 shows a image of X-ray mammogram of the breast and Figure 1(b) shows the image of Digital Mammogram of the breast.

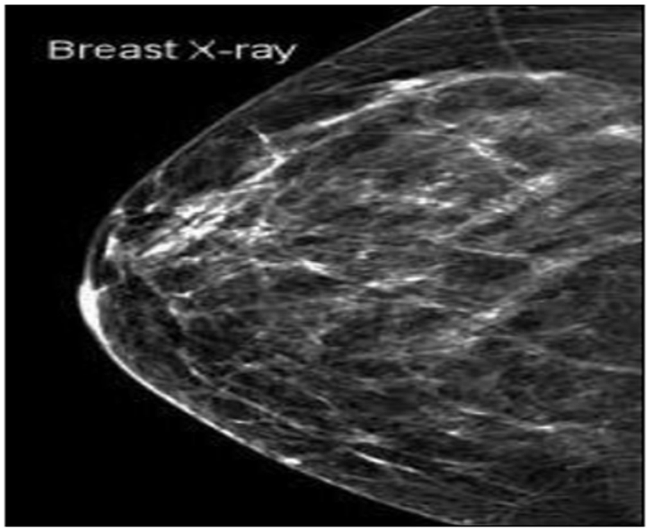


Figure 1: (a) X-ray mammogram of the breast


Figure 1(b) Digital Mammogram of the breast [4].

Calcifications, both macro and micro, can indicate breast abnormalities and may or may not be linked to cancer, with micro-calcifications visible on mammograms often requiring further assessment by radiologists [6]. Biopsy remains the definitive method for cancer confirmation. Efforts to enhance mammograms include Computer-Aided Diagnosis (CAD) systems and 3D mammography, aiming to improve lesion detection and disease assessment.

Optimization techniques like Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC) are utilized to develop efficient algorithms for breast cancer detection. Various methods, including Support Vector Machine (SVM), Artificial Neural Network (ANN), and Discrete Wavelet Transform (DWT) [5], have been explored for breast cancer detection, each with its limitations and advantages, often constrained by data availability and computational complexity.

## 2. METHODOLOGY

### 2.1 Design Approach

The research aimed to enhance breast cancer detection in mammograms using a combination of Back Propagation Neural Network (BPNN) and Particle Swarm Intelligence (PSO). The methodology involved several stages as depicted in Figure 2:

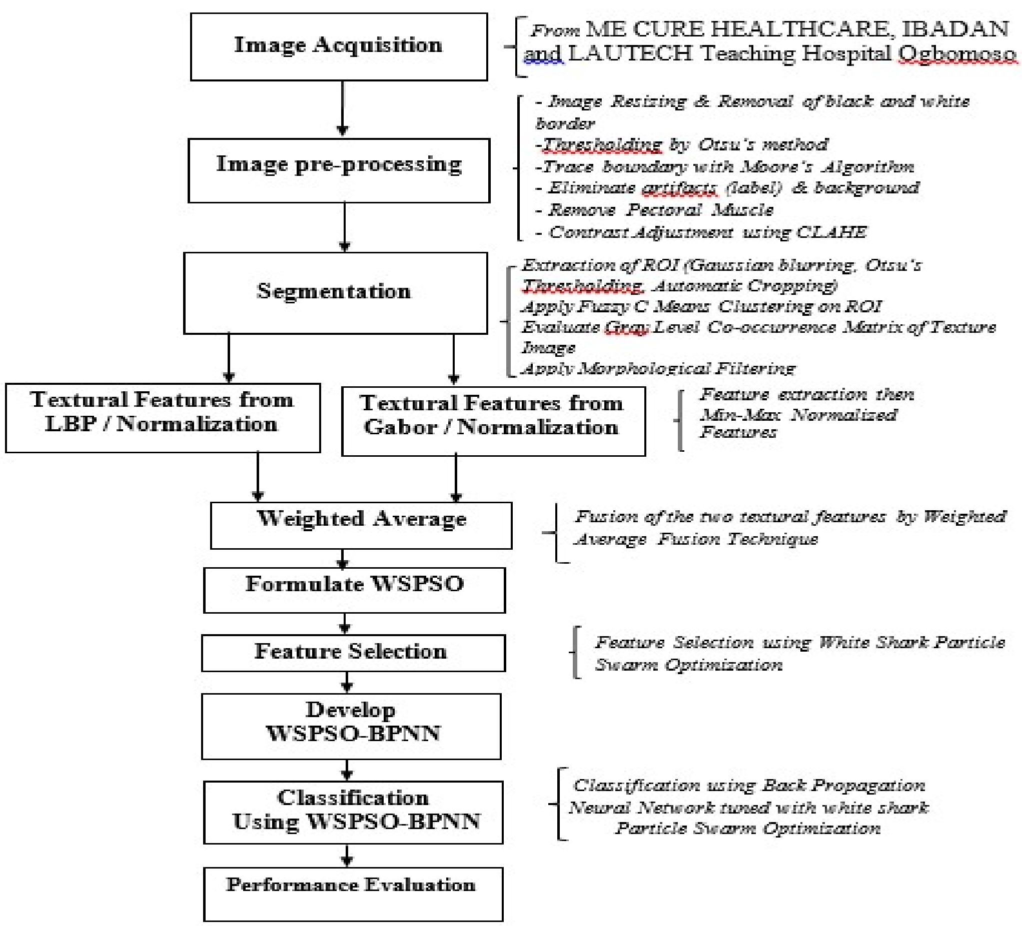


Figure 2: Block Diagram for the Structure of the Developed Technique

Image Acquisition: Mammogram datasets were sourced from ME CURE Healthcare in Ibadan and LAUTECH Teaching Hospital in Ogbomoso. Sample mammogram images are shown in figure 3.

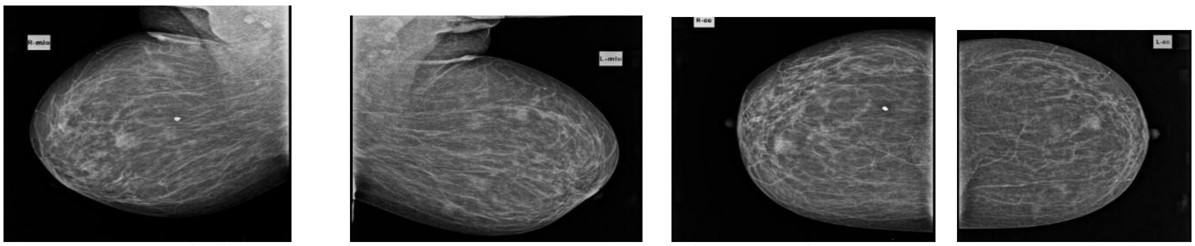

Figure 3: Sample Mammogram Images acquire from Me Cure Healthcare

## 2.2 Image Pre-processing

Image resizing, thresholding with the Otsu method, boundary tracing using Moore's Algorithm, artifact and background elimination, and removal of pectoral muscles were implemented to enhance image quality and establish an elongated trail network for further analysis. The Contrast Adjustment stage involved normalizing image contrast and enhancing image quality using Contrast Limiting Adaptive Histogram Equalization (CLAHE). For Image Segmentation the Pre-processed images underwent Otsu's thresholding for boundary localization. Automatic cropping was applied, followed by Fuzzy C-means clustering on the Region of Interest (ROI) and texture evaluation using GLCM.

Feature Extraction was carried out and textural features were extracted using Local Binary Patterns (LBP) and Gabor filters. Weighted Average Fusion Technique was carried out with the extracted features from LBP and Gabor methods and were fused using a weighted average fusion technique.

## 2.3 Development of Particle Swarm Optimization-Based Back propagation Neural Network for Classification: The BPNN-PSO classifier was trained and optimized using PSO.

The research developed an optimized back propagation neural network using Particle Swarm Optimization (PSO). Steps included defining the neural network architecture, initializing a swarm of particles with random weights and biases, and evaluating fitness through mean squared error. Personal best positions were updated, if current fitness surpassed them, while the global best position was determined from all individual best positions. Particle velocity and position were adjusted based on personal and global bests, aiming for a balance between exploration and exploitation. This process iterated until termination conditions were met, such as reaching a maximum iteration or satisfactory fitness value. The study considered a neural network with n input features, k1 and k2 hidden units, and m output units. Weights between input and hidden units were denoted as $w_{ij}^{(1)}$ and $w_{ij}^{(2)}$. The weight between the second hidden unit i and output unit j was termed as $w_{ij}^{(3)}$. Input vectors were expanded with a constant term, similarly for output from hidden layers. The excitation of hidden units and their activation functions were computed, utilizing a sigmoid function. The output layer's result represented the overall recognition output, allowing straightforward computation of information flow within the network through matrix operations.

### 2.4 Formulation of White Shark Particle Swarm Optimization Technique as Feature Selection

The White Shark Particle Swarm Optimization (WSPSO) method was devised to enhance feature selection within the standard PSO framework due to challenges such as premature convergence and sensitivity to parameters. By incorporating white shark behavior, WSPSO aimed to balance exploitation and exploration effectively, optimizing feature combinations and BPNN parameters. In WSPSO, adjustments were made to the velocity component, utilizing a modified velocity clamping technique inspired by white shark behavior, ensuring controlled exploration and exploitation without limiting particle movement within the search space. This approach was implemented to select optimal features from fused feature sets.

### 2.5 Development of White Shark Particle Swarm Optimization based Back Propagation Neural Network for Classification

This section focuses on developing a White Shark Particle Swarm Optimization (WSPSO) based Back Propagation Neural Network (BPNN) for classification tasks. The network architecture consists of input variables, hidden units, and output units.

The weights between the units are defined, and the BPNN algorithm is outlined in steps:

- Initialization of weight matrices connecting input to hidden units and hidden to output units.
- Utilization of a sigmoid activation function to determine the activation of hidden units.
- Calculation of the activation of hidden units across layers using vector-matrix multiplication.
- Application of the sigmoid function to each element of the resulting vector to determine the activation of units in the output layer.
- Computation of the network's output, representing the overall recognition output.

These steps enable straightforward computation of information flow within the network through matrix operations, facilitating classification tasks

### 2.6 Simulation of the Developed Technique

The developed technique was implemented using MATrix LABoratory (MATLAB R2016a) software on Windows 10 Enterprise 64-bit operating system, Intel®Core ™ i7-250M CPU @2.60GHZ Central Processing Unit, 4GB RAM and 500 Gigabytes hard disk drive. A user-friendly graphical interface was developed with mammogram images from ME CURE HEALTHCARE and LAUTECH Teaching hospital. Furthermore, statistical analysis was performed using IBM SPSS Statistics version 21.

### 2.7 Evaluation Measures

Performance metrics such as false positive rate, sensitivity, specificity, precision, and accuracy were computed from the confusion matrix to evaluate the efficacy of the developed technique.

## 3. RESULTS AND DISCUSSION

### 3.1 Results

The analytical results for the mammogram image categorization using the white shark particle swarm optimization-based back propagation neural network are shown in this part. The BPNN, PSO-BPNN and WSPSO-BPNN training and testing processes are illustrated graphically in Figures 4 and 5 of the User Interface. Based on the previously described categories of mammogram image (Malignant and

Benign) datasets, the technique's evaluation results are determined. Feature selection technique such as the developed WSPSO and existing PSO were employed at the feature level fusion, and BPNN were used as the classification technique. The threshold value had an impact on the technique's performance. The optimal outcomes were achieved with a threshold value of 0.75 across all techniques.

### 3.2 Analyzing Outcomes with the Malignant Dataset

The outcomes of the BPNN, PSO-BPNN and WSPSO-BPNN technique applied to the performance measures utilizing malignant datasets are shown in Table 1. The BPNN technique yielded a 16.67% false positive rate, 90.18% sensitivity, 83.33% specificity, and 88.13% accuracy in 68.76 seconds, as the Table illustrates, that is, without employing any feature selection at the feature fusion level. In addition, the PSO-BPNN technique yielded a 8.33% false positive rate, 93.75% sensitivity, 91.67% specificity, and 93.13% accuracy in 44.03 seconds. Similarly, in 32.38 seconds, the WSPSO-BPNN approach produced a 2.08% false positive rate, 96.43% sensitivity, 97.92% specificity, and 96.88% accuracy. According to Table 1's results, the WSPSO-BPNN approach demonstrated better performance compared to the PSO-BPNN technique across accuracy, sensitivity, specificity, and false positive rate metrics.

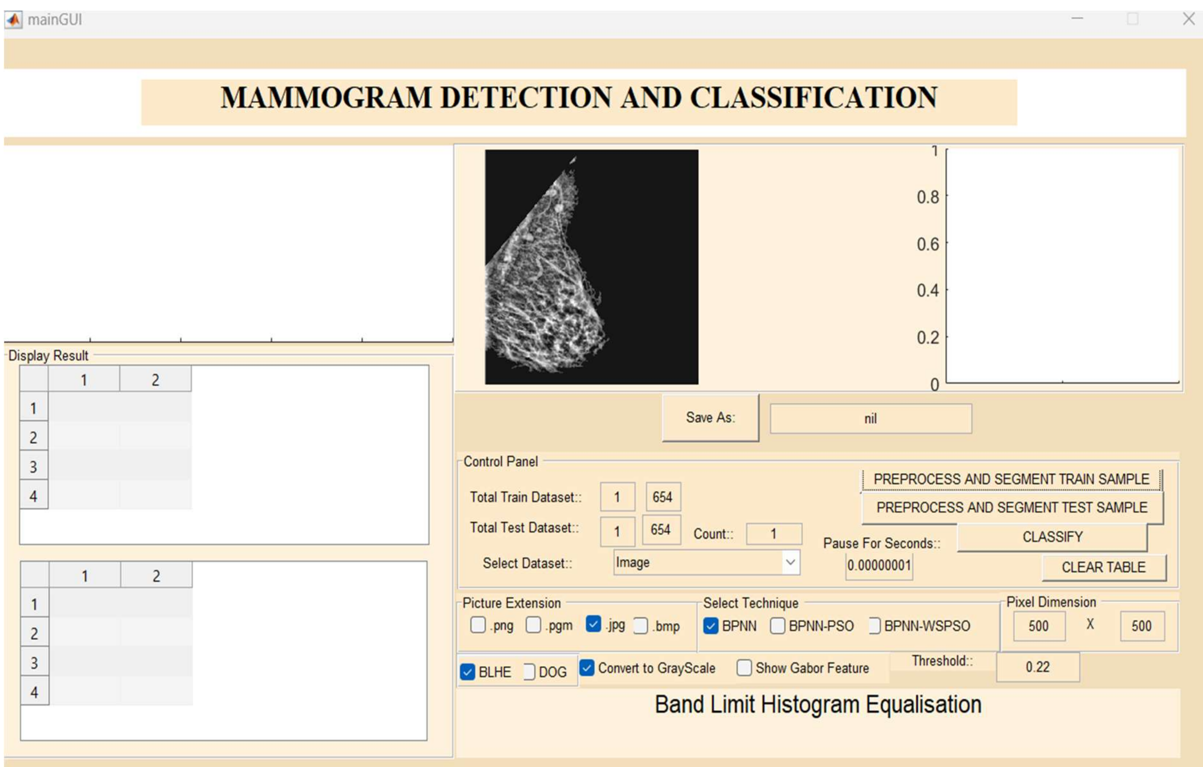


Figure 4: GUI showing the Training Process

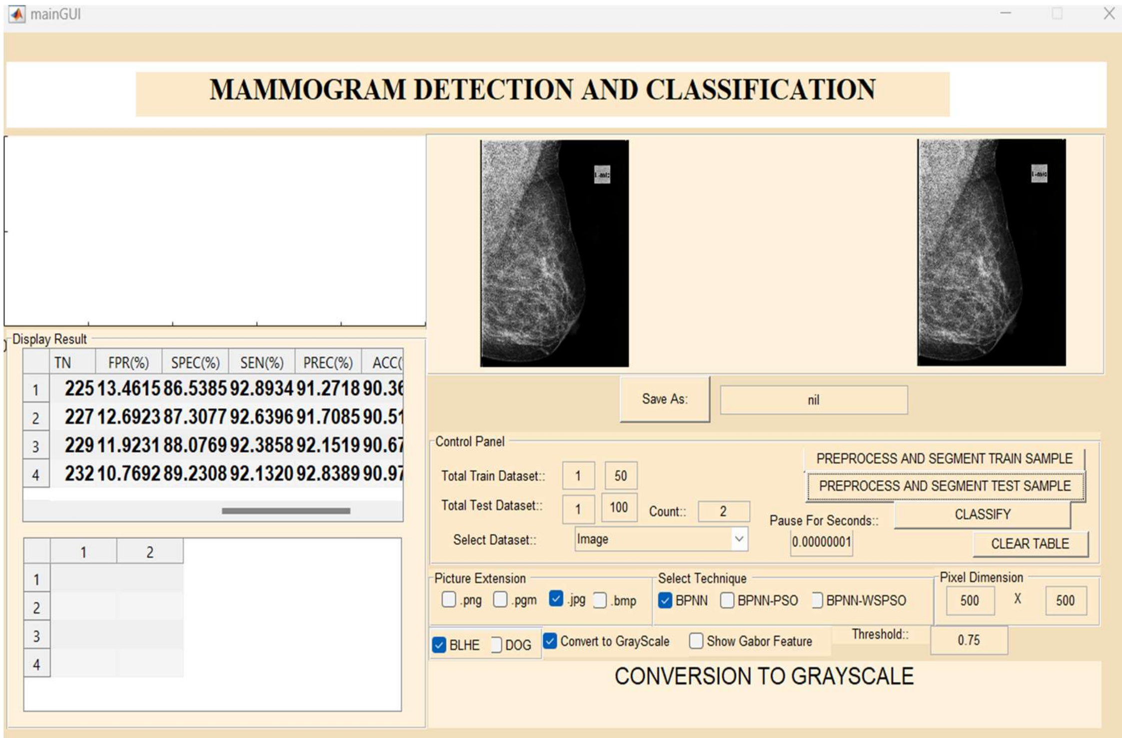


Figure 5: GUI showing the Testing Process

Table 1: Results Using The Bpnn, PSO-BPNN And WSPO-BPNN Methods On Datasets Including Malignant Data.

| Technique | FPR (%) | Specificity (%) | Sensitivity (%) | Precision (%) | Accuracy (%) | Computational Time (secs) |
|---|---|---|---|---|---|---|
| BPNN | 16.67 | 83.33 | 90.18 | 92.66 | 88.13 | 68.76 |
| PSO-BPNN | 8.33 | 91.67 | 93.75 | 96.33 | 93.13 | 44.03 |
| WSPSO-BPNN | 2.08 | 97.92 | 96.43 | 99.08 | 96.88 | 32.38 |

### 3.2 Analyzing Results with the Benign Dataset

The BPNN, PSO-BPNN and WSPSO-BPNN approach findings for the performance metrics using Benign datasets are shown in Table 2. A false positive rate of 8.57%, sensitivity of 94.51%, specificity of 91.43%, and accuracy of 93.59% at 61.94 seconds were all attained by the PSO-BPNN technique, according to the table. The WSPSO-BPNN method also produced results at 40.04 seconds with a false positive rate of 4.29%, sensitivity of 96.34%, specificity of 95.71%, and accuracy of 96.15%. According to Table 4.2's results, the WSPSO-BPNN approach performed better than the PSO-BPNN technique in terms of accuracy, sensitivity, specificity, and false positive rate. The WSPSO technique was able to select the best feature representation for accurate breast cancer classification.

Table 2: Results Obtained By The BPNN, PSO-BPNN And WSPSO-BPNN Technique With Benign Datasets.

| Technique | FPR (%) | Specificity (%) | Sensitivity (%) | Precision (%) | Accuracy (%) | Computational Time (secs) |
|---|---|---|---|---|---|---|
| BPNN | 14.29 | 85.71 | 92.07 | 93.79 | 90.17 | 84.58 |
| PSO-BPNN | 8.57 | 91.43 | 94.51 | 96.27 | 93.59 | 61.94 |
| WSPSO-BPNN | 4.29 | 95.71 | 96.34 | 98.14 | 96.15 | 40.04 |

### 3.3 Discussion of Results

The WSPSO-BPNN achieved faster breast cancer classification rates compared to PSO-BPNN and BPNN due to its balance between exploration and exploitation inherent in standard PSO. Modifications in standard PSO reduced dimensionality and enhanced global optimum search, thus improving computational efficiency and feature selection. Evaluation results show WSPSO-BPNN outperforming PSO-BPNN in accuracy, specificity, and sensitivity across Benign, and Malignant datasets. Enhanced performance is attributed to WSPSO's optimized feature selection, achieved through modifications in fitness function and velocity components, resulting in improved classification outcomes.

## 4. CONCLUSION

The key components of the WSPSO-BPNN approach in mammogram image detection and classification system were assessed in this research. A total of 1097 images from different dataset categories: Malignant and Benign datasets were employed to evaluate the efficacy of the proposed approach. The research investigated and improved the capability of PSO for feature selection by developing a WSPSO to achieve selection of relevant features and achieving better classification performance with BPNN. This research has successfully achieved an improved version of PSO by application of white shark optimizer for modifying the velocity component which was introduced to standard PSO to produce a significant and balanced feature, increase the classification performance, and avoid stagnation at local optima. The developed classification technique (WSPSO-BPNN) was examined and compared with standard PSO-BPNN and BPNN technique.

The new WSPSO-BPNN approach demonstrated enhanced accuracy, false positive rate, sensitivity, computational time, and specificity in all conducted tests and explains why the modified technique performed better than the other strategies examined in this study. The findings of the statistical study confirmed that the performance of the WSPSO-BPNN technique and PSO-BPNN differs significantly. This indicates that improving the performance of systems for mammogram image detection and classification was achieved more effectively through the implementation of the WSPSO-BPNN technique.

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