



A New Breast Cancer Detection Using Bio-Inspired Deep Neural Network.

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ABSTRACT

One of the most frequent diseases among women is breast cancer. Early identification, individualized treatment plans, and improved knowledge are essential for cancer patients to survive. The Digital Database for Screening Mammography (DDSM) dataset was applied in this research with a deep learning network and a standard CNN. We proposed Convolutional Neural Networks (CNNs) and CNN with Hybrid Particle Swarm Gray Wolf Optimization Algorithm (HPSGWA) for breast mass identification. Pretrained CNN and CNN with HPSGW architectures extract complex characteristics from the images and boost identification rates since classification in medical imaging requires the occurrence of different characteristics. An automated CNN for classification issues using the HPSGW metaheuristic algorithm. By automatically changing hyperparameters such the no. of layers, kernels, batches, and epochs, the network was built. The optimum hyperparameter, which provides the ideal value, was used to build the last CNN. Regarding accuracy, loss rate, and duration, CNN with HPSGW performed better than CNN. CNN with HPSGW achieved 99.31% of an accuracy, 0.1442 of a loss rate, and 4.12 minutes of a time conception.

Keywords: Breast Cancer, Hybrid Particle Swarm Gray Wolf Optimization Algorithm (HPSGWA), Convolutional Neural Networks (CNNs), Classification.



1. INTRODUCTION

Worldwide, cancer is one of the leading effects of death for women. More people have died from it than from other illnesses like malaria or tuberculosis. 17.1 million new instances of cancer are reported each year globally, giving to the World Health Organization (WHO) offices for cancer research. By 2040, the WHO predicts around 27.5 million new cases of cancer and 16.3 million cancer-related deaths [1].

Cancer cells in the breast can spread to the lymph nodes and harm other body organs, such as the lungs. Ductal dysfunction frequently marks the beginning of breast cancer. Milk-producing duct dysfunction is a more frequent starting point for breast cancer. Nevertheless, it can also start in breast tissue, lobules, and other glandular structures [2]. Also, the researchers discovered that adjustments to lifestyle, environment and hormone levels raise the risk of breast cancer [2], [3]. Low-dose X-ray imaging of the breast is employed to see the interior anatomy of the breast. Medical terminology for this procedure is mammography. It is estimated to be the most effective strategy for finding breast cancer. Mammography exposes the breast significantly lesser radiation dosage than previously employed technology [4],[5].

Combining deep learning (DL) and traditional machine learning (ML) methods, new work has been done on detecting breast cancer [6],[7]. This work aimed to introduce the reader to breast cancer literature and the latest

developments in the detection of breast cancer utilizing multi-view digital mammography (DMs). The study aimed to draw attention to the difficulties of using multi-view digital mammography data to apply DL for early breast cancer detection [8],[9]. We then share some thoughts and comments on the current outstanding issues after presenting the most recent research that has addressed these issues. There are two main sections to this analysis. While the second half focuses on DL approaches with a focus on multi-view mammographic data [10], the first part briefly introduces the various processes of a standard ML method. The current DL literature may be defined for the multi-view digital mammography data lesion categorization, detection, and discrimination of breast density in breast cancer [11]-[13].

2. Related Work

Hybrid bio-inspired WOA-APSO algorithm is recommended for choosing optimum features [13]. By including linear discriminant analysis in the characteristic's selection process, it is possible to determine the reduced dimensions of subsets. Analysis of two different performances is offered. Examine the results compared to several classification methods, including CNN, ANN, and support vector machines (SVM). The hybrid WOA APSO algorithm's computing efficiency is analyzed using traditional WOA and APSO methods. Automated lung tumor identification is superior to other cutting-edge techniques in terms of 97% of sensitivity, 98.66% of specificity, and 97.18% of accuracy, among



other quality metrics.

The swarming behaviours of bees, ants, fish, and birds served as the inspiration for the global optimization techniques employed in bio-inspired computing [14]. The Artificial Bee Colony Algorithm [15] is a popular bio-inspired algorithm [16] that is reliable, simple to use, and requires minimal input variables. For training Recurrent Neural Networks (RNN), the Global Guided Artificial Bee Colony (GGABC) technique has been recommended. To forecast the patient's breast cancer status, the GGABC algorithm was utilised. The best and most directed honey bees in the world were used to imitate the strategy in their searching activity. The GGABC method was shown to converge to the best solution quicker than the ABC, Guided ABC, and Global ABC with increased accuracy, according to the simulation comparison study.

BATELM is a bio-inspired model that is the first research of non-image breast cancer image processing [17]. It combines the Bat algorithm (BAT) with Extreme Learning Machines. We inspired to create a model that can accurately and efficiently forecast medical data using BAT and ELM, which has numerous benefits over other algorithms in their field. 95.7% of accuracy as attained in this report, with an RMSE of 0.32. In research report II, our aim was to determine the timing of a reappearance. The results for this example showed a 93.75% accuracy rate with a 0.30 RMSE. Tanh's function proved to be more effective in both situations. A novel hybrid technique that combines lion optimization with cat swarm

optimization provides the best threshold value for effective many level picture segmentation [18]. A novel fitness value utilizing the Otsu function and Yager's entropy too provided for more reliable outcomes. Initially, an analysis of the CEC 2017 benchmark suite is executed. The efficiency of the created segmentation approach is next analyzed. Lastly, the ANN was implemented to determine the ideal clusters. For Histopathological breast pictures, the classifier gave results with 93.23 % of a sensitivity, 93.12 % of a specificity, and 71.4% of an accuracy.

CNN is often employed in image classification applications. However, it can be challenging to identify appropriate hyperparameters and topologies [19]. This recommended, use the genetic algorithm and PSO to locate suitable hyperparameters and topologies for the FC layers (fully connected) of 3 cutting-edge CNNs: ResNet-50, DenseNet-201, and VGG-16. For all three networks, researchers got F1 scores above 0.90, an increase from the VGG-16's F1 score of 0.66 to 0.92. Comparing our results to those of other research, they also raised the ResNet-50's F1 score for the test data from 0.83 to 0.90. The BIOA, PSO, and GA algorithms [20] are applied to categorize breast thermography pictures from the DMR-IR collection to determine if a patient has cancer. The work increased F1-score for Densenet using the GA from 0.92 to 1 and for Resnet utilizing PSO from 0.85 to 0.92 for F1-score [21]. Moreover, the surrogate approach takes into account a shorter training period.



A brand-new end-to-end deep learning technique for classifying breast cancer from histopathology images called the Multi-scale Dual Residual RNN [22]. This model provides a divergent strategy of dual residual block mixed with the recurrent network to solve the vanishing gradient problem even when the network is intense. The work uses a sample called BreakHis, and it outperformed state-of-the-art approach with excellent accuracy on all the photos taken into account at different magnification stages. The application of image segmentation and pre-processing images results in improved pictures. It contributes to improving the system's overall accuracy [23]. The research evaluates the trade-off between accuracy and training time for networks developed in distinct execution environments, namely TensorFlow and MATLAB, as its conclusion.

Even with a small training data, the improved CNN can reliably categorize the observed cell nuclei. The pre-trained system is sensibly thorough, and the extracted features are pre-processed to improve classification accuracy. The MITOS samples supplied for the MITOS-ATYPIA [24] competition 2014 and the samples from the Regional Cancer Centre, Thiruvananthapuram, India, are used to assess the CNN. According to tests, the pre-trained CNN model outperforms commonly employed detection methods and offers, at minimum, a 15% F-score increase over other cutting-edge techniques. Most extract low- or mid-level characteristics, limiting the classification's accuracy. They found that high-level features

improve diagnosis, and the most popular model for obtaining high-level features is CNN [25] [26]. They recommend combining the feature extraction and classification tasks using a CNN architecture. They implemented our recommended network to the MIAS and DDSM datasets and got accuracy results of 99.074% and 99.267%, which they consider the highest recorded.

3. Proposed Methodology

This segment explains the mathematical experiment used in HPSGW and the idea behind it. As well as creating an automated CNN for classification issues using the HPSGW metaheuristic algorithm. By autonomously altering hyperparameters such the no. of layers, kernels, batches, and epochs, the network was built. The optimum hyperparameter, which provides the ideal value, was used to build the last CNN.

The PSO and GWO techniques' main computations have not changed due to the development of the HPSGW algorithm. PSO approach can fix almost all real-world bugs successfully. But there must be a means to determine the probability that the local minimum will trick the PSO. The approach to decrease the likelihood of falling into a local minimum, the GWO is employed to assist PSO. The PSO algorithm shifts those elements with a low probability of success into random places to avoid local minima. In order to reduce these risks, the GWO research capacity is used to transport those components to locations where the GWO technique has



massively improved the number of sites available. Nevertheless, the running time is enhanced using the GWO approach to supplement the PSO algorithm. The PSGW Algorithm under consideration combines the two functions.

$$A \rightarrow \alpha = | B1.Z \rightarrow \alpha - k * Z \rightarrow (t) | \rightarrow (1)$$

$$A \rightarrow \beta = | B2.Z \rightarrow \beta - k * Z \rightarrow (t) | \rightarrow (2)$$

$$A \rightarrow \delta = | B3.Z \rightarrow \delta - k * Z \rightarrow (t) | \rightarrow (3)$$

To update the velocities, Equations 4 and 5 integrate PSO and GWO variations.

$$u_j(s + 1) = v * (u_j s + d1r1(y_1 - y_j s) + d2r2(y_2 - y_j s) + d3r3(y_3 - y_j s)) \rightarrow (4)$$

$$y_j(s + 1) = y_j s + u_j(s + 1) \rightarrow (5)$$

The fitness function is employed to select an ideal value that is optimum. In the proposed hybrid optimization method, the Rosen Brock and the objective functions are used to calculate the fitness function. Adopting an suitable coordinate structure without via any gradient data otherwise creating local approximation concepts $g(y)$ successfully optimizes the Rosen Brock function, providing the given Equation 6.

$$g(y) = \sum_{j=1}^{N-1} 100(y_{j+1} - y_j^2)^2 + (1 + y_j)^2 \rightarrow (6)$$

Hybrid Particle Swarm Gray Wolf Optimization Algorithm

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Set Gray wolf population. Z; (j=1, 2, . . n)
Set A, a, C and v
Set an agent of n wolves' locations E [1,0].
Based on the fitness function achieve the a; β; δ results.
Estimate the fitness of agents by applying Equation (6)
While (s < Maximum epoch)
For every population
end
Compute the velocity applying Equation (4)
Compute the location of agents applying Equation (3)
Compute A, a, C and v
Estimate all elements with the objective function.
Compute the locations of the 3 suitable agents a, β, d
end while
s=s+ 1
    
```

The aim of this research is to purpose a hybrid PSGW method to construct a CNN architecture with high performance. The network architecture must have the following parameters.

1. Number of filters was applied to the feature map extraction.
2. kernel or filter size for each convolution
3. The number of convolutional layers.
4. By "batch size," we indicate the number of input pictures that each training block of CNN processed.

The "training and optimization" block, the most crucial component of the whole procedure and where the CNN model is initially set up to work in conjunction with



parameter optimization utilizing the HPSGW, is depicted as the proposal's major topic in Figure 1. After the HPSGW is initialised with the parameters intended for execution, particles are generated. As every agent represents an

ideal potential solution and every region will have a parameter value that must be tuned, every agent represents a complete CNN training.

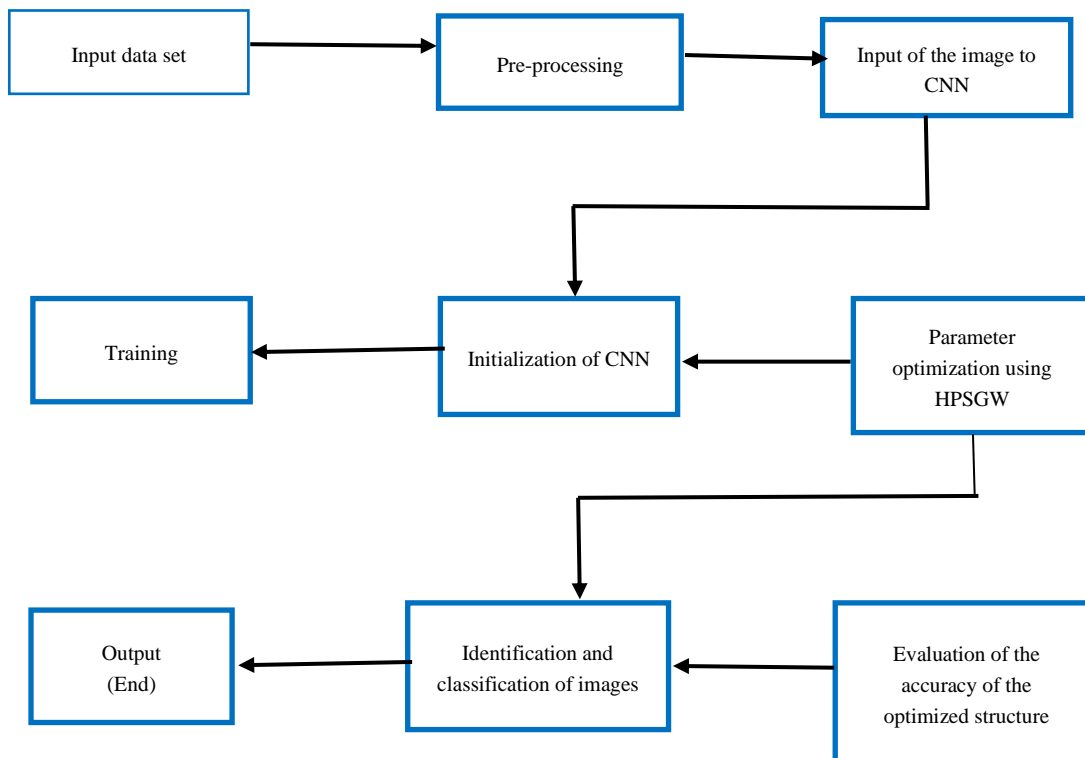


Figure 1: CNN with HPSGW Algorithm

Iterative cycles comprise the training process, completed by the HPSGW evaluating every agent produced throughout each cycle. Size of the database, size of the population, HPSGW epoch count, and agents count in each epoch all contribute to the higher processing cost. The CNN model training method is executed 500 times if HPSGW process is run 100 times with five agents. The following are the stages for applying the CNN with HPSGW Algorithm.

1. Load the training procedure's breast cancer datasets. The dataset should be scaled, colored, and resized before training.
2. Population generation for HPSGW. The population parameters are the number of agents, the weight of inertia, the number of iterations, the number of agents, and the accelerator aspects (A1, A2, A3).



3. The attributes acquired by HPSGW - the layers count, size of filter, the number of filters, and batch size are employed to establish the CNN architecture.
4. CNN model validation and training. To provide accurate results for each model,
5. Determine the goal function (fitness for each agent).
6. Update the specifications. Each agent modifies their position and velocity with each successive iteration.

CNN delivers and processes the source pictures gathered from training, validation, and testing levels. These findings will serve as an immediate step toward the objective function of the HPSGW

7. Unless the stop conditions are satisfied, this process is repeated.
8. The CNN is method using the most optimum (fitness) value.

The hyper-tuning procedure of CNN utilizing HPSGW is shown in Figure 2 using a flowchart.

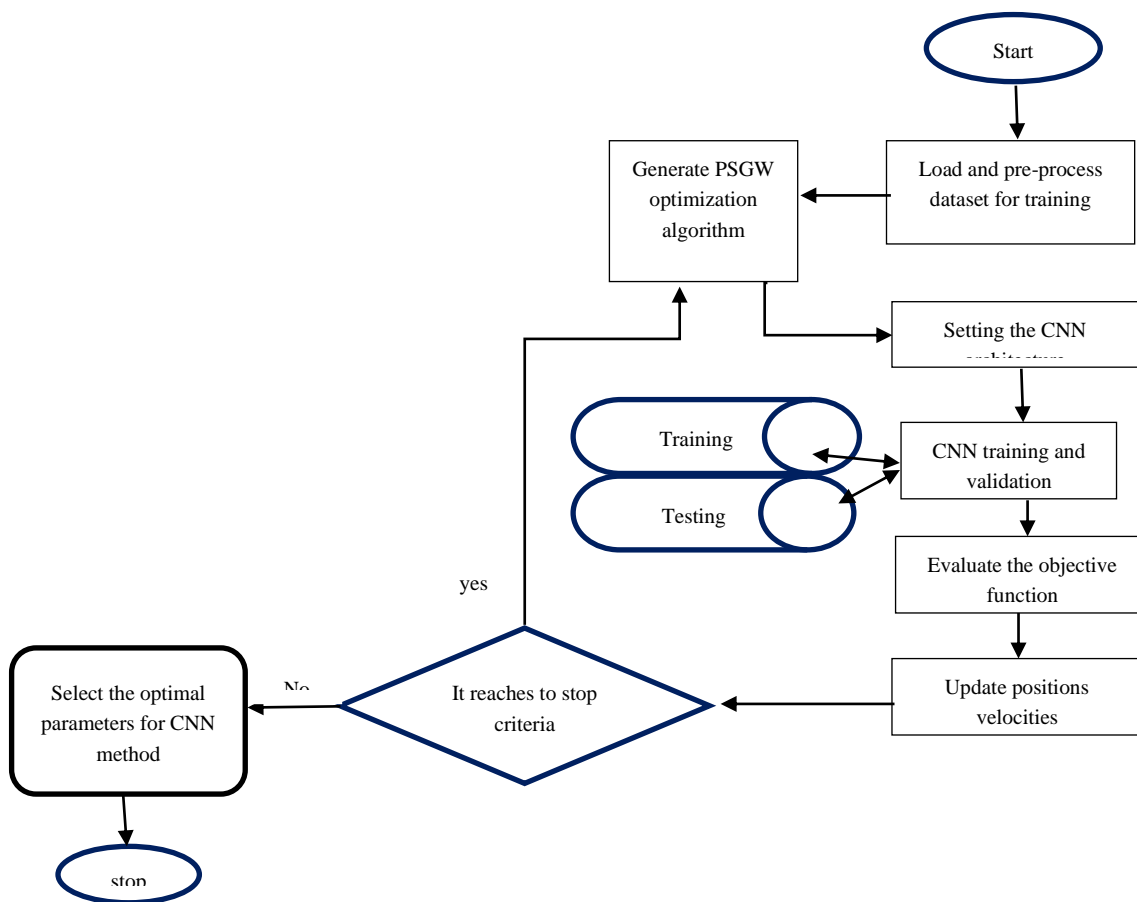


Figure 2: Flow Chart of HPSGW



4. Result and Discussion

Based on their retrieved characteristics and related labels, CNN and CNN with HPSGW classifiers were trained to divide the DDSM breast cancer dataset into 3 classes: regular, benign, and malignant. The test photos were categorized using this trained network as breast cancer diagnosis images. Other imaging techniques can often make it challenging to discern images of soft tissue. Yet, our proposed detection method effectively identifies and localizes some cancer. A contrast-enhanced MRI is the most accurate technique to see brain and spinal cord cancers. The method used in the current study may determine physically if a cancer is cancerous using processed images.

The pre-processed images are used for 70% of training and 30% of testing for CNN and CNN with HPSGW classifiers. Table 1 lists the CNN and CNN with HPSGW recognition rates.

Parameters	CNN	CNN with HPSGW
Accuracy	97.2	99.31
Loss rate	0.1962	0.1442
Time conception	6.63	4.12

Table 1: Performance’s evaluation of CNN and CNN with HPSGW

The maximum recognition rate of the pre-trained network created using CNN with an optimizer with a learning rate of 0.001 was employed to compare the outcome of different

networks. The identification rates for CNN and CNN with HPSGW are displayed in Figure 3. Because of its robustness and parallel training in the layer, CNN with HPSGW performed better than CNN with quick convergenc

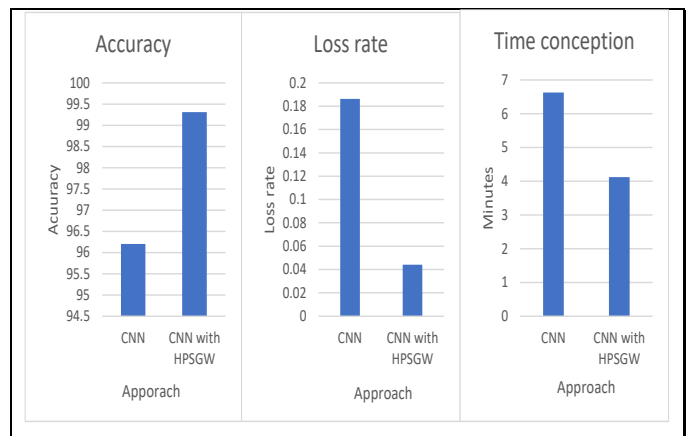


Figure 3: Comparison of accuracy, loss rate and time conception.

5. Conclusion

This study proposed a deep neural convolution network called CNN with HPSGW for identifying breast cancer. A DDSM benchmark dataset, including regular, benign, and cancer images, was used to perform the recognition procedure. Accuracy, loss rate, and runtime were used to evaluate CNN's performance with HPSGW. Using the CNN with an optimizer with a learning rate of 0.001, these techniques generated a recognition accuracy of around 99.31%. According to research, despite having a low learning rate, the average recognition rate is high. The time of conception was 4.12 minutes, and the loss rate was likewise low. The CNN with HPSGW achieves a reduced loss rate of 0.1442 breast cancer identification system compared to the 0.1962 produced by the CNN classifiers. Hence, the experimental



findings demonstrate that CNN with HPSGW outperforms CNN in advanced evaluating, good accuracy, less loss rate, and time conception for breast cancer identification compared to the traditional approach for the DDSM dataset.

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