Journal of Information & Optimization Sciences
ISSN 0252-2667 (Print), ISSN 2169-0103 (Online)
DOI : 10.47974/JIOS-1939

Towards early breast cancer detection using equilibrium optimizer algorithm

Mohammad Moradi †
Department of Electrical and Biomedical Engineering
ACECR Institute of Higher Education
Isfahan Branch
Isfahan 8418155759
Iran

Abdalhossein Rezai *
Department of Electrical Engineering
Faculty of Engineering
University of Science and Culture
Tehran 1461968151
Iran

Ali Sadollah §
Department of Mechanical Engineering
Faculty of Engineering
University of Science and Culture
Tehran 1461968151
Iran

Abstract

Breast cancer has an important role in mortality among women. Early and accurate diagnosis is essential for effective treatment. The Computer-Aided Detection (CAD) system can assist healthcare professionals in the diagnostic process. This research introduces a practical approach to enhance the CAD system's performance in breast cancer diagnosis by analyzing thermal images. The research methodology in the suggested CAD system involves the integration of efficient algorithms during the feature extraction and classification stages,

† *ORCID-ID:* 0009-0007-0310-8999
* *ORCID-ID:* 0000-0001-8529-499X
§ *ORCID-ID:* 0000-0002-7782-4126

† *E-mail:* Mohamadmoradi0078@gmail.com
* *E-mail:* rezai@usc.ac.ir (Corresponding Author)
§ *E-mail:* sadollah@usc.ac.ir

along with a novel feature selection algorithm. The SFTA technique is employed for feature extraction. Then, the EO algorithm is applied to the extracted features. The SVM and DTree classification techniques are then implemented to assess the discriminative efficacy of the selected features, aiming for successful group classification. The suggested method is evaluated using the DMR database. The results demonstrate an accuracy of 98.5%, specificity of 99%, and sensitivity of 98%. The breast cancer diagnostic method that was developed exhibits advantages over other approaches that utilize thermography.

Subject Classification: *68U10, 54H30, 92C55.*

Keywords: *Breast cancer, Equilibrium-optimizer algorithm, Feature selection, Thermography, Computer-aided detection system, Feature extraction.*

1. Introduction

Breast Cancer (BC) has a vital role in mortality among women, which underscores the critical importance of accurate and early diagnosis for effective treatment. Early detection not only aids in averting unnecessary surgeries but also enhances the likelihood of a patient's survival. Cancerous tissues exhibit heightened metabolic activity, increasing blood flow and elevated temperatures. In this context, infrared breast thermography serves as a screening tool, capturing temperature distribution in breast tissue. It proves pivotal in mammography screening for early BC detection [1, 2].

The use of a Computer-Aided Detection (CAD) system for analyzing breast thermal images has proven to be a valuable asset, supporting radiologists in cancer diagnosis [3]. The CAD system comprises various stages such as Feature Extraction (FE), classification, and Feature Selection (FS) [4]. Among these, the FS emerges as a crucial step, as it not only reduces processing time but also enhances diagnostic accuracy by selecting optimal features [2].

Artificial Intelligence (AI) algorithms represent a significant category within metaheuristics, drawing inspiration from natural processes. In the natural world, collective behaviors observed in animals like hawks, bats, whales, and bees surpass the intelligence of individual members [5-7]. Researchers have harnessed these AI behaviors to address complex problems with incomplete information [8]. One notable instance of AI algorithms is the Equilibrium Optimizer (EO), explicitly employed for optimization applications [9-11].

In recent years, there have been multiple endeavors to introduce CAD systems for BC diagnosis, incorporating AI algorithms and thermography

[1, 9, 12-19]. While these CAD systems exhibit commendable performance, there remains room for improvement in the BC detection [2, 13, 20, 21].

This study proposes a practical approach for enhancing the efficiency of the CAD systems dedicated to BC diagnosis through the thermography technique. The primary contributions of this paper include the following:

- FE utilizing the Segmentation Fractal Texture Analysis (SFTA) technique.
- FS employing the EO algorithm on the extracted features.
- Application of Support Vector Machine (SVM) and Decision Tree (DTree) classification algorithms to categorize the selected feature groups.
- Comparative analysis indicates that the proposed method exhibits advantages over other BC diagnosis approaches.

This essay's organization is as follows: Section 2 introduces the previous works. Section 3 offers the developed method. Section 4 introduces the utilized algorithms. Section 5 presents the results. Section 6 represents the findings. Finally, section 7 describes the essay's conclusion.

2. Related Works

A BC CAD system has been proposed by Zarei, Rezai, and Hamidpour [1]. They use a novel Gaussian Mean Shift (GMS) algorithm-based segmentation technique for thermal images. The resulting accuracy, specificity, and sensitivity are 87.4%, 84.86%, and 91.81%, respectively.

FS algorithms have been utilized by Darabi, Rezai, and Hamidpour [12] to diagnose BC in thermal imaging. Their suggested CAD system uses a hybrid approach for FS that combines the Random Subset Feature Selection (RSFS) method with the Genetic Algorithm (GA) and mRMR algorithm. Additionally, the SVM and kNN classifiers are used. The achieved specificity, accuracy, and sensitivity are 75%, 79.31%, and 85.36%, respectively.

Essential features in thermal imaging for diagnosing BC have been the focus of Salimian et al. [9]. They examined several features: mean, correlation, energy, entropy, and contrast.

Using supervised and unsupervised methodologies, Resmini et al. [13] have created a computational approach for cancer diagnosis that combines dynamic and static infrared thermography. The GA has been made available for the FS. They tested their approach using the DMR database. They also employed SVM for the classification. The achieved specificity is 95%, accuracy is 95%, and sensitivity is 95%.

Moayedi, Rezai, and Hamidpour [14] have provided a way to enhance the CAD system's performance using thermal images. The suggested method extracts features using thermal images and the LBP and GLCM. The Firefly FS algorithm is then used to select the best features. They employed the DTree, SVM, and kNN classifiers to identify BC. When employing SVM as a classifier, they obtained a sensitivity of 99%, accuracy of 98.8%, and specificity of 98.2%.

To diagnose, Khafaga et al. [15] employed thermal images and extracted features using the algorithms VGG16Net, VGG19Net, ResNet-50, GoogLeNet, and AlexNet. The obtained results are 98.36% sensitivity, 62.51% specificity, and 96.15% accuracy.

A thorough examination of the impact of FS approaches on detecting and diagnosing anomalies in thermographic images is carried out by Mishra and Rath [16]. The study selects features using principal component analysis and autoencoder techniques. The DMR database is used for the assessment, and the kNN method is used for classification. The results show a 95.45% accuracy rate.

Pramanik, Pramanik, and Sarkar [17] proposed a CAD system to diagnose BC. They utilized GA and Grey Wolf Optimizer (GWO) algorithms for feature selection. The accuracy rates achieved using GA and GWO algorithms are 100%.

Kaladevi et al. [18] employed the Orca Predation Optimization (OPO) algorithm for detecting BC from thermal images. They evaluated the proposed CAD system using datasets from the curated breast imaging subset of DDSM. The achieved accuracy, specificity, and sensitivity are 99.04%, 98.56%, and 97.78%, respectively.

Chatterjee et al. [22] used the algorithm Grunwald-Letnikov-aided Dragonfly for BC detection and achieved an accuracy of 97% with SVM classification.

Kalaiyarasi et al. [23] utilized the Ant Colony Optimization (ACO) and FS algorithm, as well as the SVM algorithm for BC detection, achieving an accuracy of 97.4%.

Hamim et al. [24] utilized the ACO Algorithm for BC detection in the field of gene selection and achieved an accuracy of 95%.

Punitha, Al-Turjman, and Stephan, [25] applied the Artificial Bee Colony (ABC) and Integrated Artificial Immune System (IAIS) algorithms for FS in BC detection from the Wisconsin database, achieving an accuracy of 99.11%.

3. Methodology

Figure 1 illustrates the research approach outlined in this paper.

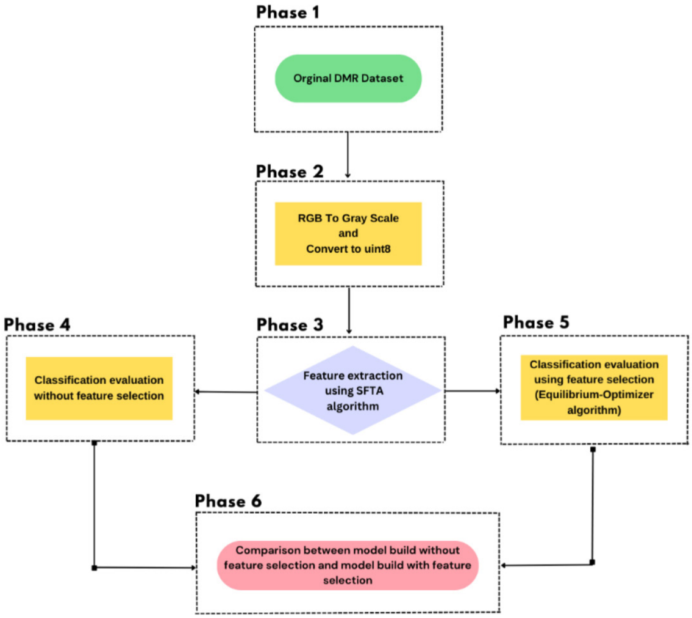

Figure 1

Research Methodology

Our research methodology comprises six phases. The initial phase involves data acquisition, where the necessary data for the study is collected. The second stage focuses on data preprocessing, encompassing tasks such as integration, cleaning, and transformation to render the collected data suitable for classification prediction. The third phase involves feature extraction, and the obtained results transition to phase four, where classification prediction is performed without feature selection. In phase five, we introduce the EO algorithm, which is used for FS, and the obtained results are subsequently employed for classification. Then, the suggested models, with and without FS, are compared in the final stage.

3.1 *Phase 1 – Dataset*

A set of 200 images from both healthy and malignant patients is obtained using the DMR database [26].

3.2 *Phase 2 – Data Preprocessing*

An essential preprocessing step in this phase is changing the format from RGB to black and white. Finally, the format is changed to unit8. The brightness level of the images is changed to between 0 and 255.

3.3 *Phase 3 – Feature Extraction*

FE is performed using the SFTA algorithm, yielding 576 features per image. As a result, 115,200 features are extracted.

3.4 *Phase 4 – Classification Evaluation Without FS*

The classification is executed without FS in this step. The SVM and DTree algorithms are employed for this purpose. While all extracted features are utilized to detect cancer.

3.5 *Phase 5 – Classification Evaluation Using FS*

Recognizing that the accuracy may be decreased by utilizing all features due to high processing. The FS is introduced in this phase to reduce processing time and enhance accuracy. The EO algorithm is used for FS and applied to the extracted features.

4. Applied Algorithms

4.1 *FE Algorithm*

We employ the SFTA for FE. This algorithm comprises two stages. In the first stage, a grayscale image undergoes decomposition to a binary image set using Two Threshold Binary Decomposition (TTBD). Subsequently, the pixel count and mean gray level are calculated for each image. Furthermore, the boundaries of the regions are leveraged to compute the fractal dimensions.

4.2 *FS Algorithm*

FS plays a crucial role in data mining, analysis, and AI. This essay introduces an efficient hybrid EO-based [27] FS algorithm. The EO algorithm is an optimization algorithm based on dynamic systems' balance and equilibrium behaviors [28]. The EO algorithm is based on a simple, well-mixed dynamic Mass Balance (MB) that controls volume. This entails using an MB equation to show how concentrated a nonreactive material is in a control volume while considering its several sink and source mechanisms. The equation for MB represents the fundamental physics that controls the mass conservation in a control volume, including mass generated, exiting, and entering. An ordinary differential equation of first order indicates the generic MB equation shown in Eq. (1) [28].

$$V\frac{dz}{dt} = QZ_{eq} - QZ + G \tag{1}$$

According to this formula, the mass-produced internally, the total mass entering the system, less the mass exiting the system, represents the change in mass over time [28]. Parameter Z represents the concentration inside the control volume (V). The term $V\frac{dz}{dt}$ is a representation of the mass change rate in the V. The parameter Q represents the volumetric flow rate out of and into the V. The parameter Z_{eq} denotes the concentration at equilibrium when no generation is inside the V. The parameter G represents the mass generation rate inside the V. More details about the EO algorithm can be found in [28]. Algorithm 1 illustrates the EO algorithm.

4.3 *Classification Algorithm*

In this section, we apply the DTree and SVM algorithms on the extracted or selected features to analyze the performance of the proposed models. The following provides a concise overview of each algorithm:

4.3.1 The SVM Algorithm

One significant classification algorithm is the SVM algorithm, which establishes a connection between inputs and outputs based on labeled cases. It categorizes inputs, and its operation relies on nonlinear kernel functions [29].

4.3.2 The DTree Algorithm

The decision tree uses a tree structure to build classification models. It gradually separates a dataset into smaller subsets while concurrently creating a DTree. Leaf nodes and decision nodes make up the final tree. The decision nodes have two or more branches, but the leaf nodes show categories. In a DTree, the root node represents the best prediction. Because of their versatility, DTrees can handle both numerical and categorical data [30].

Algorithm 1: The EO algorithm

Set the initial populations of the particles, i=1,...n.
Give the equilibrium candidates' fitness a high number.
Set unrestricted parameters GP=0.5; a1=2; a2=1;
While Iter < Max_iter
  For i=1: n
    compute fitness of ith particle
    If fit($\vec{Z}_i$) < fit($\vec{Z}_{eq\,1}$)
      Replace with and $\vec{Z}_{eq\,1}$ with ($\vec{Z}_i$) and fit ($\vec{Z}_{eq\,1}$) with fit($\vec{Z}_i$)
    Elseif fit($\vec{Z}_i$) > fit($\vec{Z}_{eq\,1}$) & fit($\vec{Z}_i$) > fit($\vec{Z}_{eq\,2}$)
      Replace with and $\vec{Z}_{eq\,2}$ with ($\vec{Z}_i$) and fit ($\vec{Z}_{eq\,2}$) with fit($\vec{Z}_i$)
    Elseif fit($\vec{Z}_i$) > fit($\vec{Z}_{eq\,1}$) & fit($\vec{Z}_i$) > fit($\vec{Z}_{eq\,2}$) & fit($\vec{Z}_i$) < fit($\vec{Z}_{eq\,3}$)
      Replace with and $\vec{Z}_{eq\,3}$ with ($\vec{Z}_i$) and fit ($\vec{Z}_{eq\,3}$) with fit($\vec{Z}_i$)
    Elseif fit($\vec{Z}_i$) > fit($\vec{Z}_{eq\,1}$) & fit($\vec{Z}_i$) > fit($\vec{ZC}_{eq\,2}$) & fit($\vec{Z}_i$) < fit($\vec{Z}_{eq\,3}$) &
fit($\vec{Z}_i$) < fit($\vec{Z}_{eq\,4}$)
      Replace with and $\vec{Z}_{eq\,4}$ with ($\vec{Z}_i$) and fit ($\vec{Z}_{eq\,4}$) with fit($\vec{Z}_i$)
    End (If)
  End (for)
    $\overrightarrow{Z_{ave}} = \frac{\vec{Z}_{eq\,1} + \vec{Z}_{eq\,2} + \vec{Z}_{eq\,3} + \vec{Z}_{eq\,4}}{4}$
Construct the equilibrium pool $\vec{Z}_{eq,pool}$ =
{$\vec{Z}_{eq(1)}$, $\vec{Z}_{eq(2)}$, $\vec{Z}_{eq(3)}$, $\vec{Z}_{eq(4)}$, $\vec{Z}_{eq(ave)}$
    Accomplish memory saving (if Iter > 1)
    Assign $t = (1 - \frac{Iter}{Max_{iter}})^{(a_2 \frac{Iter}{Max\_iter})}$ Eq(9)
  For i=1: n
    Select one candidate at random from the vector (equilibrium pool)
    Generate random vectors of $\vec{\lambda}$, $\vec{r}$ from Eq(11)
    Construct $\vec{F} = a_1 \mathrm{sign}\left(\vec{r} - 0.5\right)[e^{-\vec{\lambda} t} - 1]$
    Construct $\overrightarrow{GCP} = \begin{cases} 0.5r_1, & r_2 < GP \\ 0, & r_2 \geq GP \end{cases}$
    Construct $\vec{G}_0 = \overrightarrow{GCP}\,(\overrightarrow{C_{eq}} - \vec{\lambda}\,\vec{C})$
    Construct $\vec{G} = \vec{G}_0 . \vec{F}$
    Update concentrations $\vec{Z} = \vec{Z}_{eq} + \left(\vec{Z}_0 - \vec{Z}_{eq}\right) . \vec{F} + \frac{\vec{G}}{\vec{\lambda} V}(1 - \vec{F})$
  End (for)
    Iter =Iter+1
End While

5. Results and Discussion

The proposed CAD system is assessed using MATLAB 2019a, employing the DMR database. The evaluation considers classification sensitivity, accuracy, and specificity as effectiveness measures, as given by Eqs. (2)-(4):

$$Accuracy = \frac{TN+TP}{TN+TP+FN+FP} \tag{2}$$

$$Sensitivity = \frac{TP}{TP+FN} \tag{3}$$

$$Specifity = \frac{TN}{FP+TN} \tag{4}$$

Here, TN, FN, FP, and TP denote true negatives, false negatives, false positives, and true positives, respectively. The subsequent sections present the obtained experimental results and engage in a detailed discussion of the outcomes.

5.1 *Classification Evaluation Without FS-phase*

In this section, we apply the DTree and SVM to the DMR dataset to classify without using FS. Figure 2 shows the experimental outcomes regarding sensitivity, accuracy, and specificity.

The results without FS demonstrate that the DTree classification provides better performance regarding sensitivity, accuracy, and specificity.

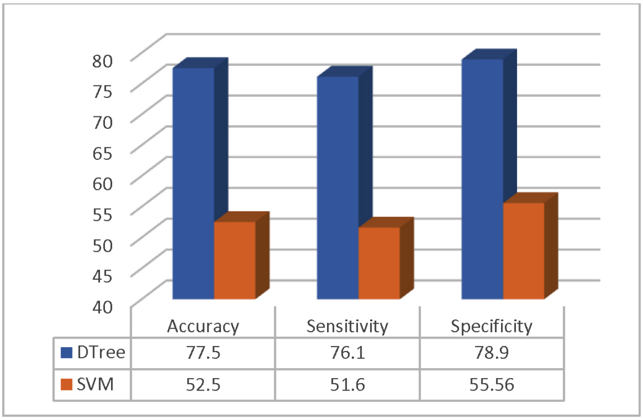

Figure 2

The results without FS

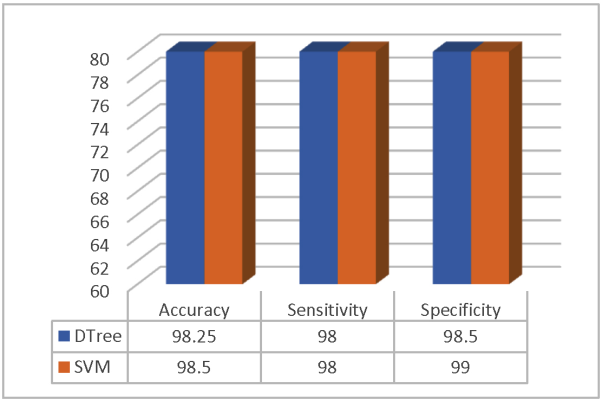

Figure 3

The results using EO-FS

5.2 *Classification Evaluation with FS-phase*

The classification is done using the EO algorithm as the FS algorithm in this section. The results are shown in Figure 3.

The results using the EO-FS algorithm indicate that the SVM classification provides high performance regarding accuracy and specificity.

6. Comparative Analysis

Figure 4 illustrates the results. According to the results illustrated in Figure 4, the maximum accuracy rate reached is 98.5%. These findings

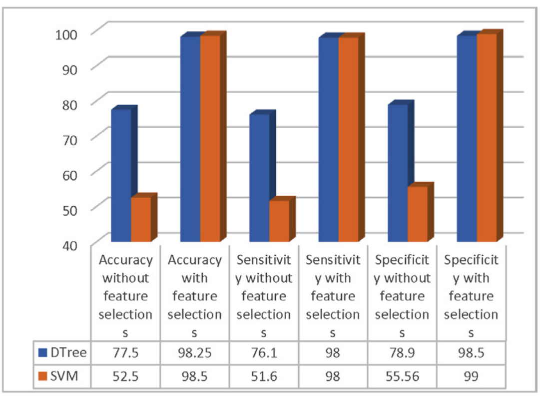

Figure 4

The experimental results of classifications

signify the comprehensive efficacy of the SVM classification algorithm employing the EO-based FS algorithm.

Table 1 encapsulates the results, facilitating a more nuanced comparative analysis. Furthermore, Table 2 summarizes the experimental results, including the CAD systems' accuracy, specificity, and sensitivity metrics.

Table 1
Performance of classifiers

Evaluation Metrics	Classifiers			
	DTree		SVM	
	Without Feature Selection	Using EO Feature Selection	Without Feature Selection	Using EO Feature Selection
Accuracy (%)	77.5	98.25	52.5	98.5
Sensitivity (%)	76.1	98	51.6	98
Specificity (%)	78.9	98.5	55.56	99

Table 2
Comparative table for the CAD systems

Ref	Database	FS method	Classifier	Performance (%)
[14]	*DMR*	Firefly	SVM	*Specificity = 98.2%* *Accuracy = 98.8%* *Sensitivity = 99%*
[22]	*DMR*	Grunwald-Letnikov-aided Dragonfly	SVM	Accuracy = 97%
[16]	DMR	GLRLM	kNN	Specificity = 88.07% Accuracy = 95.45% Sensitivity = 99.17%
[24]	ELVIRA	ACO	SVM	Accuracy = 95%
[25]	Wisconsin	IAIS and ABC	ANN	Accuracy = 99.11%
[23]	*DMR*	ACO and PSO	SVM	Accuracy = 97.4%
[31]	DMR	BPSO	SVM	Accuracy = 96.22%
[12]	DMR	mRMR, GA and RSFS	SVM	Accuracy = 79.31% Specificity = 75% Sensitivity = 83.36%

Contd...

[13]	DMR	GA	SVM	Specificity = 95% Accuracy = 95% Sensitivity = 95%
This paper	DMR	EO	DTree	Specificity = 98.5% Accuracy = 98.25% Sensitivity = 98%
			SVM	Specificity = 99% Accuracy = 98.5% Sensitivity = 98%

The outcomes highlight the commendable performance of the proposed CAD system. Remarkable results were attained, with the system achieving a peak accuracy, specificity, and sensitivity of 98.5%, 99%, and 98%, respectively. These findings stand out favorably compared to other investigations targeting BC detection through thermography using the SVM classifier algorithm.

7. Conclusions

Thermography, recognized for its non-invasiveness, painlessness, cost-effectiveness, and potential for significant treatment opportunities, stands out as a preferred technique for BC detection. This paper introduced an innovative method to enhance the detection of BC accuracy using infrared thermal images. The EO algorithm proves to be highly effective in selecting optimal features, contributing to the reduction of diagnostic process complexity. Evaluation results show the success of the FS algorithm, achieving an accuracy of 98.5%, specificity of 99%, and sensitivity of 98%. Comparative analysis underscores the superiority of the suggested CAD system over other existing CAD systems.

References

[1] M. Zarei, A. Rezai, and S. S. Falahieh Hamidpour, "Breast cancer segmentation based on modified Gaussian mean shift algorithm for infrared thermal images," *Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization,* vol. 9, no. 6, pp. 574-580, 2021/11/02 (2021), doi: 10.1080/21681163.2021.1897884.

[2] M. Moradi and A. Rezai, "High-performance breast cancer diagnosis method using hybrid feature selection method," *Biomedical Engineering/Biomedizinische Technik*, vol. 70, no. 2, pp. 171–181 (2025).

[3] Angela N. Giaquinto, Hyuna Sung, Kimberly D. Miller, Joan L. Kramer, Lisa A. Newman, Adair Minihan, Ahmedin Jemal and Rebecca L. Siegel "Breast Cancer Statistics, 2022," *CA: A Cancer Journal for Clinicians,* vol. 72, no. 6, pp. 524-541, 2022/11/01 (2022), doi: https://doi.org/10.3322/caac.21754.

[4] R. Iacob, E. R. Iacob, E. R. Stoicescu, D. M. Ghenciu, D. M. Cocolea, A. Constantinescu, L. A. Ghenciu, and D. L. Manolescu, "Evaluating the Role of Breast Ultrasound in Early Detection of Breast Cancer in Low- and Middle-Income Countries: A Comprehensive Narrative Review," *MDPI Journal,* vol. 11, no. 3, p. 262 (2024). [Online]. Available: https://www.mdpi.com/2306-5354/11/3/262.

[5] D.-D. Ramírez-Ochoa, L. A. Pérez-Domínguez, E.-A. Martínez-Gómez, and D. Luviano-Cruz, "PSO, a Swarm Intelligence-Based Evolutionary Algorithm as a Decision-Making Strategy: A Review," *Symmetry*, vol. 14, no. 3, doi: 10.3390/sym14030455.

[6] K. Pradhan and P. Chawla, "Medical Internet of things using machine learning algorithms for lung cancer detection," vol. 7, no. 4, pp. 591-623 (2020).

[7] M. Arunkumar and K. A. Kumar, "GOSVM: Gannet optimization based support vector machine for malicious attack detection in cloud environment," vol. 15, no. 3, pp. 1653-1660 (2023).

[8] C. Kaushal, K. Kaushal, and A. C. M. Singla, "Firefly optimization-based segmentation technique to analyse medical images of breast cancer," vol. 98, no. 7, pp. 1293-1308 (2021).

[9] M. Salimian, A. Rezai, S. Hamidpour, and F. Khajeh-Khalili, *Effective Features in Thermal Images for Breast Cancer Detection* (2019).

[10] H. Myriam, A. A. Abdelhamid, E. M. El-Kenawy, A. Ibrahim, M. M. Metwally Eid, and M. M. Jamjoom, "Advanced meta-heuristic algorithm based on Particle Swarm and Al-biruni Earth Radius optimization methods for oral cancer detection," vol. 11, pp. 23681-23700 (2023).

[11] A. Das and M. N. Mohanty, "Transformation of 1-D data to 2-D image using stochastic mapping method for secured skin lesion detection," *Journal of Information and Optimization Sciences*, vol. 43, no. 8, pp. 1915-1923, 2022/11/17 (2022), doi: 10.1080/02522667.2022.2103294.

[12] N. Darabi, A. Rezai, and S. S. F. Hamidpour, "Breast Cancer Detection Using Rsfs-Based Feature Selection Algorithms in Thermal Images," *Biomedical Engineering: Applications, Basis and Communications*, vol. 33, no. 03, pp. 2150020, 2021/06/01 (2021), doi: 10.4015/S1016237221500204.

[13] R. Resmini, L. Faria da Silva, P. R. T. Medeiros, A. S. Araujo, D. C. Muchaluat-Saade, and A. Conci, "A hybrid methodology for breast screening and cancer diagnosis using thermography," *Computers in Biology and Medicine*, vol. 135, pp. 104553, 2021/08/01/ (2021), doi: https://doi.org/10.1016/j.compbiomed.2021.104553.

[14] S. M. Z. Moayedi, A. Rezai, and S. S. F. Hamidpour, "Toward effective breast cancer detection in thermal images using efficient feature selection algorithm and feature extraction methods," *Biomedical Engineering: Applications, Basis and Communications*, pp. 2450007 (2024).

[15] D. S. Khafaga, A. A. Alhussan, E. M. El-kenawy, A. E. Takieldeen, T. M. Hassan, E. A. Hegazy, E. A. Fattah Eid, A. Ibrahim and A. A. Abdelhamid, "Meta-heuristics for Feature Selection and Classification in Diagnostic Breast Cancer," *Computers, Materials \& Continua*, vol. 73, no. 1 (2022), doi: 10.32604/cmc.2022.029605.

[16] V. Mishra and S. K. Rath, "Detection of breast cancer tumours based on feature reduction and classification of thermograms," *Quantitative InfraRed Thermography Journal*, vol. 18, no. 5, pp. 300-313, 2021/10/20 2021, doi: 10.1080/17686733.2020.1768497.

[17] R. Pramanik, P. Pramanik, and R. Sarkar, "Breast cancer detection in thermograms using a hybrid of GA and GWO based deep feature selection method," *Expert Systems with Applications*, vol. 219, pp. 119643, 2023/06/01/ (2023), doi: https://doi.org/10.1016/j.eswa.2023.119643.

[18] P. Kaladevi, V. V. Punitha, D. Muthusankar, and R. Praveen, "Breast cancer diagnosis using Orca predation optimization algorithm,"

Journal of Intelligent & Fuzzy Systems, vol. 45, pp. 3855-3873 (2023), doi: 10.3233/JIFS-231176.

[19] A. Dureja and P. Pahwa, "Medical image retrieval for detecting pneumonia using binary classification with deep convolutional neural networks," *Journal of Information and Optimization Sciences,* vol. 41, no. 6, pp. 1419-1431, 2020/08/17 (2020), doi: 10.1080/02522667.2020.1809096.

[20] N. Razmjooy, V. V. Estrela, and H. J. Loschi, "Entropy-based breast cancer detection in digital mammograms using world cup optimization algorithm," in *Research anthology on medical informatics in breast and cervical cancer*: IGI Global, pp. 645-665 (2023).

[21] R. Gupta and S. K. Malik, "A classification using RDFLIB and SPARQL on RDF dataset," *Journal of Information and Optimization Sciences,* vol. 43, no. 1, pp. 143-154, 2022/01/02 (2022), doi: 10.1080/02522667.2022.2039461.

[22] S. Chatterjee, S. Biswas, A. Majee, S. Sen, D. Oliva, and R. Sarkar, "Breast cancer detection from thermal images using a Grunwald-Letnikov-aided Dragonfly algorithm-based deep feature selection method," *Computers in Biology and Medicine,* vol. 141, pp. 105027, 2022/02/01/ (2022), doi: https://doi.org/10.1016/j.compbiomed.2021.105027.

[23] V. Kalaiyarasi, Meenakshi, S. Jain, S. Jain, R. Umapriya, R. Sarala, and M. S. Ramkumar, "Bio-Inspired Optimization Technique for Feature Selection to Enhance Accuracy of BC Detection," in *2023 International Conference on Inventive Computation Technologies (ICICT)*, 26-28 April 2023, pp. 741-748 (2023), doi: 10.1109/ICICT57646.2023.10134478.

[24] M. Hamim, I. El Moudden, M. D Pant, H. Moutachaouik, and M. Hain, "A Hybrid Gene Selection Strategy Based on Fisher and Ant Colony Optimization Algorithm for Breast Cancer Classification," *International Journal of Online and Biomedical Engineering (iJOE),* vol. 17, no. 02, pp. 148-163, 02/12 (2021), doi: 10.3991/ijoe.v17i02.19889.

[25] S. Punitha, F. Al-Turjman, and T. Stephan, "An automated breast cancer diagnosis using feature selection and parameter optimization in ANN," *Computers & Electrical Engineering,* vol. 90, pp. 106958, 2021/03/01/ (2021), doi: https://doi.org/10.1016/j.compeleceng.2020.106958.

[26] D. Database, “https://visual.ic.uff.br/dmi/.”

[27] Y. Gao, Y. Zhou, and Q. J. I. A. Luo, “An efficient binary equilibrium optimizer algorithm for feature selection,” vol. 8, pp. 140936-140963 (2020).

[28] A. Faramarzi, M. Heidarinejad, B. Stephens, and S. Mirjalili, “Equilibrium optimizer: A novel optimization algorithm,” *Knowledge-Based Systems*, vol. 191, pp. 105190, 2020/03/05/ (2020), doi: https://doi.org/10.1016/j.knosys.2019.105190.

[29] S. V. M. Vishwanathan and M. N. Murty, “SSVM: a simple SVM algorithm,” in *Proceedings of the 2002 International Joint Conference on Neural Networks. IJCNN'02* (Cat. No.02CH37290), 12-17 May 2002, vol. 3, pp. 2393-2398 vol. 3 (2002), doi: 10.1109/IJCNN.2002.1007516.

[30] J. Capetanakis, “Tree algorithms for packet broadcast channels,” *IEEE Transactions on Information Theory,* vol. 25, no. 5, pp. 505-515 (1979), doi: 10.1109/TIT.1979.1056093.

[31] M. Fikadu, “Thermography Breast Cancer Detection Using Appropriate Segmentation and Feature Selection Approach,” (2021).

Received August, 2024