ACTA IMEKO
ISSN: 2221-870X
March 2026, Volume 15, Number 1, 1 - 11

Breast cancer detection using an ant colony-based feature selection algorithm

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ABSTRACT
Nowadays, breast cancer is a common cancer among people. Fortunately, early detection of breast cancer can save many lives. Thermography uses infrared cameras to measure temperature changes on the skin's surface. In breast cancer, tumors cause increased blood flow and higher temperatures in the affected area. These temperature changes appear as hot spots in the thermographic image. Thermography can assist in early detection of cancer, but it is not sufficient for a definitive diagnosis on its own and should be used in conjunction with other methods like mammography. This article proposes and assesses an effective approach to enhance the performance of Computer Aided Detection (CAD) systems that employ the ant colony-based swarm intelligence algorithm for breast cancer detection. The article focuses on using the Segmentation Fractal Texture Analysis (SFTA) technique for feature extraction, applying the ant colony algorithm, and the hybrid of ant colony and firefly algorithms to the extracted features to identify the most relevant ones, and classification of the selected feature groups using DTree, k-Nearest Neighbors (kNN), and Support Vector Machine (SVM) algorithms. The results indicate that the obtained accuracy, specificity, and sensitivity are 98 %, 97 %, and 99 %, respectively. The experimental results using 200 images from the Database for Mastodology Research (DMR) indicate that applying an ant colony-based feature selection algorithm can considerably enhance breast cancer detection using thermography images.

Section: RESEARCH PAPER

Keywords: breast cancer; ant colony optimization; firefly optimization; image processing

Citation: M. Moradi, A. Rezai, Breast cancer detection using an ant colony-based feature selection algorithm, Acta IMEKO, vol. 15 (2026) no. 1, pp. 1-11. DOI: 10.21014/actaimeko.v15i1.1925

Section Editor: Elisabeth Costa Monteiro, Pontifical Catholic University of Rio de Janeiro, Brazil

Received August 18, 2024; **In final form** January 26, 2026; **Published** March 2026

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1. INTRODUCTION

Breast cancer is unfortunately a common malignancy among women, but early detection and identification of the disease can save many lives. To improve detection efficiency, researchers worldwide are working on developing reliable Computer-Aided Detection (CAD) models [1], [2]. The three primary techniques used to detect breast cancer are ultrasound, mammography, and Magnetic Resonance Imaging (MRI). However, these methods are not practical for regular mass screening at short time intervals [3]-[6].

The cancerous tumours have higher metabolic activity; as a result, they have higher temperature in comparison with normal tissue. So, thermography presents a non-intrusive and cost-effective approach, suitable for regular self-screening. This renders it a hopeful remedy for the predicaments associated with prevailing diagnostic methodologies [7], [8]. The essence of this endeavour resides in its application of diverse Artificial Intelligence (AI) methodologies, yielding a diagnosis predicated on thermal images of the breast garnered from data repositories [9], [10]. Through the execution and amalgamation of these techniques, we can enhance the precision and accuracy of the breast cancer diagnosis, potentially leading to the preservation of more lives [11]. While the term “accuracy” has a well-established qualitative meaning in metrology, it is also widely used in the AI community with a different, quantitative definition as a performance indicator. In this work, the AI-related usage follows the conventional machine-learning definition and should not be confused with the metrological concept of accuracy.

Swarm Intelligence (SI) algorithms are a class of the AI algorithms that are inspired by the collective behaviour of social animals such as ants, bees, birds, fireflies, and fish. The basic idea behind the SI is that individual agents, such as ants or birds, can collectively exhibit intelligent behaviour, even though they may be relatively simple in isolation [12], [13].

The SI algorithms typically involve a group of simple agents or particles that interact with each other and their environment to find optimal solutions to a problem. These agents can communicate with one another and adapt their behaviour based on the behaviour of their neighbours [14]. By leveraging the collective intelligence of the swarm, the SI algorithms can find solutions that are often better than those found by traditional optimization methods. Illustrations of the SI algorithms encompass Ant Colony Optimization (ACO), particle swarm optimization, and artificial bee colony optimization. These algorithms have found utility across an extensive spectrum of challenges, spanning optimization, clustering, data mining, and routing within communication networks [15].

The ant colony optimization algorithm is a metaheuristic optimization algorithm that is inspired by the foraging behaviour of ants. The ACO was first introduced by Marco Dorigo in 1992 and has since been applied to a wide range of optimization problems, including routing, scheduling, and combinatorial optimization [16].

The firefly algorithm is another metaheuristic optimization algorithm that is inspired by the behaviour of fireflies. Fireflies are known for their flashing behaviour, which is used for communication and mating purposes. In the firefly algorithm, each firefly represents a potential solution to an optimization problem, and the flashing behaviour of the fireflies represents their movement towards the optimal solution [17].

The ACO and the firefly algorithm offer significant advantages over traditional algorithms, such as gradient-based methods and evolutionary algorithms. These algorithms can perform parallel and extensive searches in the solution space, avoiding local optima. ACO, with the collective behaviour of ants, excels in optimizing complex and large-scale problems, while the firefly algorithm, with its attraction mechanism, is effective for global search and multi-objective optimization. Neither algorithm requires the derivatives of the objective function, and both can adapt well to dynamic and complex environments, whereas traditional algorithms often struggle in such scenarios [18].

This research proposes and assesses an effective approach to enhance the performance of the CAD systems that employ the ant colony-based SI algorithm for breast cancer diagnosis. The research primarily focuses on the following key contributions:

a) Feature extraction using the Segmentation Fractal Texture Analysis (SFTA) technique.
b) Feature selection by applying the ant colony algorithm and the hybrid of ant colony and firefly algorithms to the extracted features to identify the most relevant ones.
c) Classification of the three selected feature groups using DTree, k-Nearest Neighbors (kNN), and Support Vector Machine (SVM) algorithms.

The remainder of this research is structured as follows: Section 2 offers an overview of related studies. Section 3 outlines the methodology adopted. Section 4 elucidates the algorithms employed. Section 5 delineates the findings of the experiments conducted. Section 6 conducts a comparative analysis of the results obtained. Ultimately, this research culminates in section 7, providing concluding remarks.

2. RELATED WORKS

Chatterjee et al. [19] utilized a deep feature selection method based on the Grunwald–Letnikov-aided dragonfly algorithm to detect breast cancer from thermal images. They employed 900 images for algorithm training and 226 images for algorithm testing. In their proposed method, they achieved an accuracy of 97 %.

In order to detect breast cancer, Khafaga et al. [20] used the feature selection method using the data-inflated Digital Twin Optimizer (DTO) algorithm. In this research, a total of 2650 breast thermal images have been used, with an accuracy of 96.8 %.

Kalita et al. [21] utilized mammography images for breast cancer detection. They employed the Local Binary Pattern (LBP) algorithm for feature extraction and the ACO algorithm for feature selection. They achieved an accuracy of 97.9 %, a sensitivity of 95.9 %, and a specificity of 97.3 %.

Sreevidya et al. [22] utilized the Multi-objective Improved Ant Colony Optimization (MIACO) algorithm for breast cancer detection from mammography images. Additionally, they employed the Deep Convolutional Neural Networks (DCNN) algorithm for classification purposes and achieved an accuracy of 99.36 %.

Kalaiyarasi et al. [23] initially focused on breast cancer detection by utilizing the GLCM algorithm for feature extraction. Subsequently, they employed the ACO and Particle Swarm Optimization (PSO) algorithms for feature selection. For classification, they used the SVM algorithm, achieving an accuracy of 97.4 %.

Reddy et al. [24] utilized the ACO algorithm for breast cancer detection using 422 mammography images, achieving an accuracy of 90.11 %

Hamim et al. [25] utilized the ACO algorithm for feature selection from thermal images of breast tissue for the breast cancer detection. They employed SVM, kNN, and C5 algorithms for classification and achieved an accuracy of 95 %.

Punitha et al. [26] performed breast cancer detection from thermal images using feature extraction with the help of the Integrated Artificial Immune System (IAIS) and the Artificial Bee Colony (ABC)-based breast cancer diagnosis algorithm. They used the Wisconsin Breast Cancer Database (WBCD). They conducted classification using the Artificial Neural Networks (ANN) algorithm, achieving an accuracy of 99.11 %.

Sharma et al. [27] offered a breast cancer detection method using feature extraction through three methods: correlation-based selection, information gain-based selection, and sequential feature selection. They used the WBCD dataset consisting of 596 images. They achieved an accuracy of 99.41 %.

Zarei et al. [1] have introduced a segmentation technique utilizing the Gaussian Mean Shift (GMS) algorithm for diagnosing breast cancer through infrared thermal images. The results achieved include an overall accuracy of 87.4 %.

Darabi et al. [14] employed feature selection algorithms on thermal images to detect breast cancer. Their CAD system employs a hybrid approach, combining the minimum Redundancy Maximum Relevance (mRMR) algorithm with the Genetic Algorithm (GA) and the Random Subset Feature Selection (RSFS) algorithm for efficient feature selection. The classification is performed using the SVM and kNN algorithms. The results achieved include an overall accuracy of 79.31 %.

Salimian et al. [9] directed their attention towards identifying impactful features in thermal images for the purpose of diagnosing breast cancer. They conducted tests on various features, including energy, entropy, correlation, contrast, and mean.

Mishra et al. [13] conducted an extensive investigation into the impact of feature selection techniques on the detection and diagnosis of anomalies in thermography images. The study employed principal component analysis and autoencoder techniques for feature selection. The evaluation was carried out using the Database for Mastology Research (DMR), with classification performed by the kNN algorithm. The results achieved include an accuracy of 95.45 %.

Fikadu et al. [28] introduced the Binary Particle Swarm Optimization (BPSO) method, which involves utilizing the BPSO algorithm for feature selection. The evaluation was conducted using the DMR, and the classification was carried out using the SVM algorithm. The achieved accuracy for this approach is 96.22 %.

Resmini et al. [29] introduced a hybrid computational approach that combines Dynamic Infrared Thermography (DIT) and Static Infrared Thermography (SIT) to screen and diagnose abnormalities related to cancer. This method involves the application of both supervised and unsupervised machine learning techniques. Feature selection was accomplished using GA. The proposed approach was tested on thermography images from the DMR database, and the SVM is employed for classification. The results achieved include an accuracy of 95 %.

Kriti et al. [30] utilized the GoogLeNet algorithm for feature extraction in order to detect breast cancer from ultrasound images. The results achieved include an accuracy of 98 %.

Yurttakal et al. [31] focused on breast cancer detection using MRI images and convolutional neural network algorithms. The results achieved include an overall accuracy of 98.33 %.

Jahangeer et al. [32] used the hybrid algorithm of series network and VGG-16 for breast cancer detection from mammography images. Using the proposed algorithm, an accuracy of 96.45 % was achieved.

Moradi and Rezai [33] improved breast cancer diagnosis on thermal images using the SFTA algorithm for feature extraction and a hybrid grey wolf and firefly optimization method for feature selection. The results show high performance, with 97 % accuracy and 98 % sensitivity.

Anas et al. [34] developed a combined YOLOv5 and Mask R-CNN model for breast cancer detection in mammography, achieving high accuracy (FPR = 0.049 %, FNR = 0.029 %, MCC = 92.02 %) and outperforming the baseline model, thereby aiding early diagnosis.

Although this research provides suitable performance, breast cancer detection method can be improved as described in this paper.

3. METHODOLOGY

Figure 1 illustrates the methodology developed in this research.

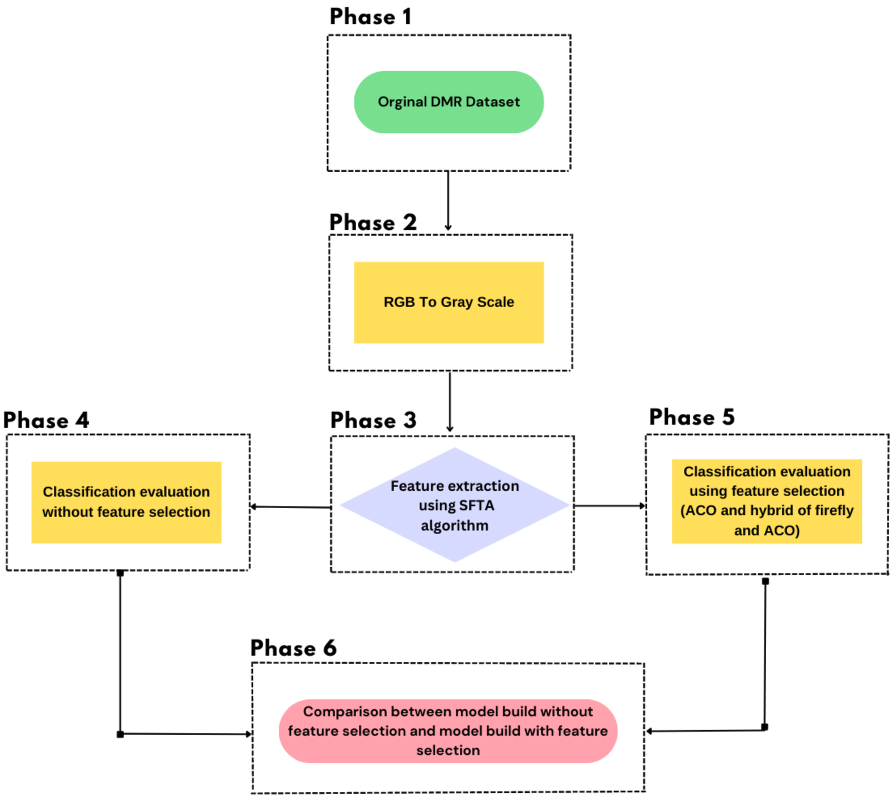


Figure 1. Research methodology.

The research was conducted in six phases. Phase 1 involved acquiring labelled images. Phase 2 involved image preparation, where the images were converted from colour to grayscale and from 16-bit to 8-bit format. In phase 3, the SFTA feature extraction technique was applied to the images. In phase 4, the classification evaluation was performed without using feature selection. In phase 5, the ant colony feature selection algorithm and the hybrid of ant colony and firefly feature selection algorithms were applied to the extracted features from the images. In phase 6, the classification of the results was compared. The details of these phases are described in the next section.

3.1. Phase 1 – Data acquisition

In this phase, breast cancer data was collected from the public DMR [35]. The dataset consisted of 200 thermal images, with 100 images for healthy people and 100 images for patients. Figure 2 and Figure 3 depict examples of images showing healthy and cancerous tissues of this database.

3.2. Phase 2 – Data preprocessing

Initially, the image format was converted from RGB to grayscale, and subsequently, it is converted to 8-bit format.

3.3. Phase 3 – Feature extraction

We utilized the SFTA technique for feature extraction. The SFTA algorithm offers several significant advantages over GLCM and LBP, particularly in the analysis of complex and irregular textures. By utilizing multi-level thresholding and fractal-based features, SFTA is capable of capturing fine structural and non-linear patterns more effectively than GLCM and LBP. Unlike GLCM, which is sensitive to multiple parameters, such as direction and pixel distance, and often generates a large set of redundant features, SFTA produces a more compact feature set, making it more suitable for lightweight and efficient machine learning models. Compared to LBP, which is primarily effective for simple and repetitive textures, SFTA demonstrates higher accuracy in detecting natural and intricate

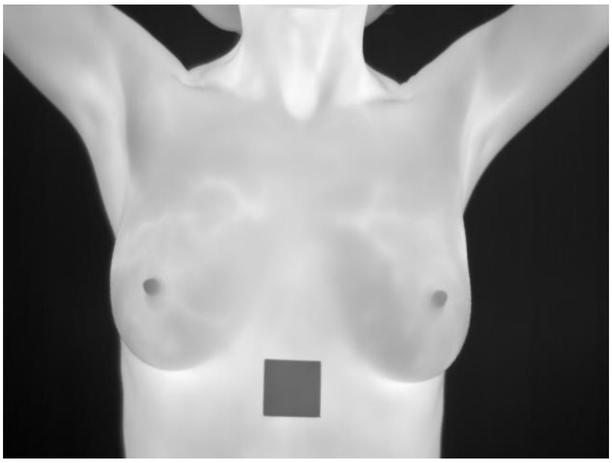


Figure 2. Healthy image.

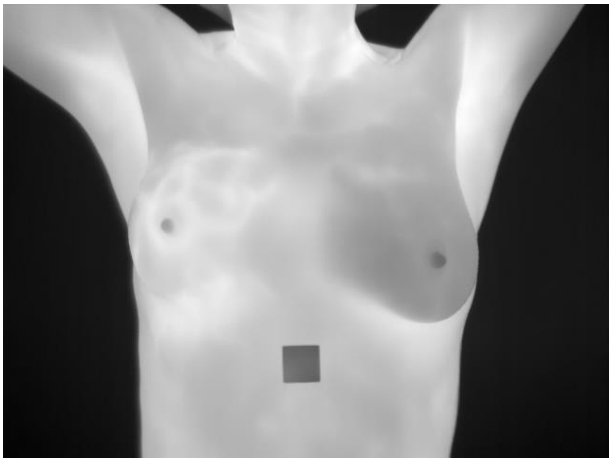


Figure 3. Cancerous image.

structures. These characteristics make SFTA a compelling choice for applications such as medical image analysis, biological texture classification, or any task involving detailed and heterogeneous image content [36]. Resulting in 576 features extracted from each image, all 115,200 extracted features were found to be useful in this step.

3.4. Phase 4 – Classification evaluation without feature selection

In this phase, we conducted classification without feature selection for comparison purposes. We employed DTree, SVM, and kNN algorithms for classification. Although all 115,200 extracted features were found to be useful in detecting cancer, the process was time-consuming due to the large number of features involved.

3.5. Phase 5 – Classification evaluation with feature selection

In this phase, we recognized that using all features may result in reduced accuracy due to high processing times, redundant features, and unnecessary features. Therefore, we decided to employ feature selection techniques to mitigate this issue and potentially increase accuracy. We proposed the use of the ant colony algorithm, and a combination of the ant colony and firefly algorithms for feature selection. These algorithms are applied to the extracted features in order to select a subset of features that would yield the best classification results. This approach aims to not only reduce processing time, but also potentially improve the accuracy of the classification model.

Table 1. Confusion matrix representation.

Actual	**Predicted**	
	Positive	**Negative**
Positive	True Positive (TP)	False Negative (FN)
Negative	False Positive (FP)	True Negative (TN)

3.6. Phase 6 – Comparative analysis

In this phase, we compared all the models, including those without feature selection and those that utilized ant colony, and the hybrid of ant colony and firefly feature selection algorithms. The effectiveness of the models is assessed using classification accuracy, sensitivity, and specificity measures. Table 1 and equations (1)–(3) are used to represent the confusion matrix and classification measures, respectively.

$$\text{Accuracy} = \frac{TN + TP}{TP + FP + TN + FN}, \quad (1)$$

$$Sensivity = \frac{TP}{TP + FN}, \quad (2)$$

$$Specifity = \frac{TN}{FP + TN}. \quad (3)$$

In the domain of breast cancer classification, the terms are as follows:

- True Positive (TP): This denotes the count of patients who truly have breast cancer and are accurately identified as such by the classification model.
- True Negative (TN): This signifies the count of patients who are genuinely healthy and are correctly classified as such by the model.
- False Positive (FP): This corresponds to the count of patients who are actually healthy but are mistakenly classified as having breast cancer by the model.
- False Negative (FN): This represents the count of patients who indeed have breast cancer yet are wrongly categorized as healthy by the model.

These metrics are employed to compute various performance indicators, such as accuracy, sensitivity, and specificity. These measures are pivotal for assessing the efficiency of the classification model in the context of breast cancer detection.

4. ALGORITHMS

4.1 Feature extraction algorithm

The SFTA method is employed for feature extraction within this research. This algorithm can be partitioned into two primary components:

1. The initial part involves applying a decomposition technique to the input grayscale images, which transforms them into a series of binary images using the Two-Threshold Binary Decomposition (TTBD) approach.
2. The subsequent step calculates the fractal dimension based on the region boundaries of each consecutive binary image.

Figure 4 provides an overview of the SFTA extraction process.

In the initial phase of the entire process, the TTBD commences by taking a grayscale image $J_{\mathrm{b}}(x, y)$ as input and

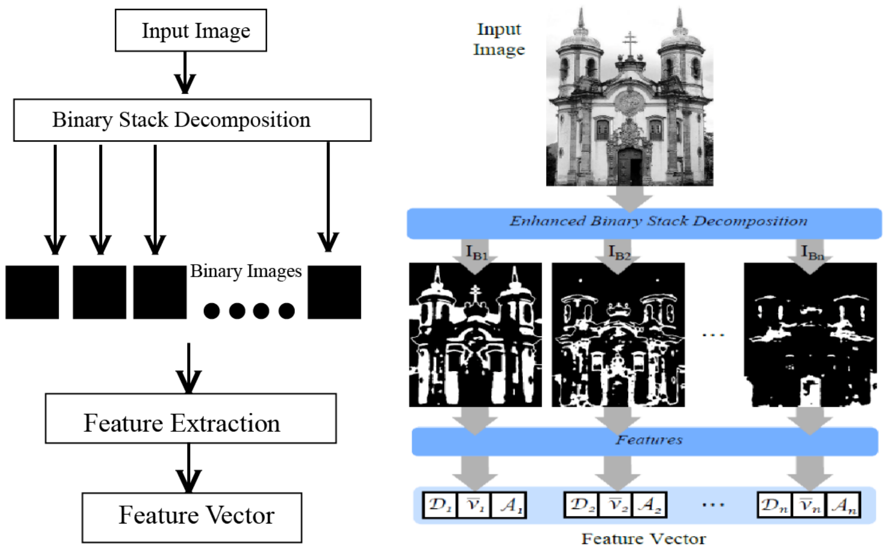


Figure 4. SFTA extraction process overview [37].

produces an array of binary images as output. This step involves the following procedure:

1. The first stride involves determining an interval T that encompasses several threshold values, which are derived by uniformly selecting grey-level values. This is accomplished through the recursive application of the multi-level Otsu algorithm.
2. Subsequently, a binary image $J_{\mathrm{b}}(x, y)$ is generated according to equation (4).

$$J_{\mathrm{b}}(x,y) = \begin{cases} 1, & \text{if } t_1 < J_{\mathrm{a}}(x,y) < t_{\mathrm{r}} \\ 0, & \text{otherwise} \end{cases}. \tag{4}$$

In this process:

- t_1 signifies the lower threshold of the grey level,
- t_{r} signifies the upper threshold.

Moving on to the second step, a vector is constructed encompassing the pixel count, mean grey level, and fractal dimensions for each binary image. The first two attributes are determined by utilizing the binary images derived through the TTBD process.

The calculation of the fractal dimensions is based on a binary image $J_{\mathrm{b}}(x, y)$, and it's manifested as a boundary image $\Delta(x, y)$. The edges of the image are computed through the following formula [37]:

$$\Delta(x,y) = \begin{cases} 1, & \text{if } \exists (x',y') \in N_8[(x,y)]: \\ & J_{\mathrm{b}}(x',y') = 0 \wedge J_{\mathrm{b}}(x,y) = 1 \\ & 0, \text{otherwise} \end{cases}, \tag{5}$$

where $N_8[(x, y)]$ denotes the set of pixels that are 8-connected to the pixel at coordinates (x, y). The value of $\Delta(x, y)$ is 1 if $J_{\mathrm{b}}(x, y)$ is equal to 1 and at least one of its neighbouring pixels is zero. Otherwise, $\Delta(x, y)$ is set to zero.

This process results in borders that are one pixel in width [37].

4.2 Feature selection algorithm

4.2.1. Ant colony optimization algorithm

The ant colony optimization algorithm is a metaheuristic technique that draws inspiration from the foraging behaviour of ants as they search for the shortest path between their nest and a food source. In this algorithm, a virtual colony of ants works together to explore potential optimal solutions for a given problem. This collaborative effort involves creating a solution graph and strategically depositing pheromone trails on it. As ants traverse the graph, they are guided by these pheromone trails, which lead them toward better solutions. This mechanism enhances the algorithm's ability to discover more effective solutions to complex problems [38].

The algorithm begins by initializing a set of virtual ants at a starting node, and then the ants construct solutions by probabilistically selecting edges to traverse based on pheromone levels and heuristics. As the ants traverse the edges, they deposit pheromones on the path they have chosen. The amount of pheromone deposited is proportional to the quality of the solution found [38].

In each iteration of the algorithm, the pheromone trails are updated based on the quality of the solutions found by the ants. The stronger the solution found by the ants, the more pheromone is deposited on the edges of the solution graph. The pheromone trails also evaporate over time, so that the search process can escape from local optima and explore new areas of the search space [38].

The ant colony optimization algorithm has demonstrated successful applications across a range of optimization problems, including but not limited to the traveling salesman problem, the vehicle routing problem, and the job-shop scheduling problem. Algorithm 1 displays the ant colony optimization algorithm [18].

Consider a scenario where m ants are linked to m randomly generated initial vectors (w^{q}, q = 1, 2, 3, ..., m) [39]. The solution vector for each ant is then adjusted using the subsequent expression as follows:

$$w_t^{\mathrm{q(new)}} = w_t^{\mathrm{q(old)}} \pm \alpha \; (t = 1, 2, \ldots, I)\,. \tag{6}$$

In this scenario, $w_t^{\mathrm{q(new)}}$ represents the solution vector of the q^{th} ant during cycle t, while $w_t^{\mathrm{q(old)}}$ stands for the solution obtained from the previous step in cycle t. Additionally, α is a randomly generated vector used to determine the length of the jump [39]. This α plays a pivotal role in preventing the search direction for the global optimum from getting stuck in unfavorable local optima. The ant vector, $w_t^{\mathrm{q(new)}}$, which is achieved in the t^{th} cycle through equation (6), is computed based on the same ant's value obtained from the previous step. Moreover, within equation (6), the (+) sign is employed when the point w_t^{q} is positioned to the left of the best solution along the x-coordinate axis. Conversely, the (-) sign is used when the point w_t^{q} is situated to the right of the best solution on the same axis. The search direction is determined by equation (7) [39]:

$$\overline{w}_t^{\mathrm{best}} = w_t^{\mathrm{best}} + w_t^{\mathrm{best}} \cdot 0.01 \tag{7}$$

If the condition $\mathrm{f}(\overline{w}_t^{\mathrm{best}}) \leq \mathrm{f}(w_t^{\mathrm{best}})$ holds true, the (+) sign is employed within equation (6). Conversely, if the condition is not met, the (-) sign is used. The ($\pm$) sign defines the search direction to reach the global optimum. The α value dictates the jump length and is progressively reduced to avoid overshooting the global optimum, as illustrated in Algorithm 1.

Algorithm 1. The ACO algorithm.

```
Initialization:
For p=1 to I (I=cycle number)
If p=1 then generate m random ants within Feasible Search Space (FSS)
      else reduce FSS with range [ w_{t-1}^{best} + β ; w_{t-1}^{best} − β]
end if
for p=1 to m
      Determine f(w_t^{best})
      save w_t^{best}
end
Pheromone update:
Pheromone evaporation
Update pheromone trail
Solution phase:
Determine search direction
Generate the values of α vector
for p=1 to m
      Determine the values of new colony
      Determine new f(w_t^{best})
      Save w_t^{best}
end
if f(w_t^{best})^{new} ≤ f(w_t^{best})^{old} then w^{globalmin} = (w_t^{best})^{new}
      else w^{globalmin} = (w_t^{best})^{old}
end if
α_t = α_{t−1} * 0.99
β_t = β_{t−1} * 0.99
end
```

At the conclusion of each cycle, a new ant colony is established, mirroring the count of ants from the preceding colony. The pheromone quantity (μ_t) is diminished to simulate the evaporation process seen in actual ant colonies, accomplished through equation (8) during the pheromone update phase. Following this reduction, the pheromone level is updated using equation (9). Notably, the pheromone quantity is only intensified around the best objective function value. This iterative process continues until the prescribed number of cycles, denoted as I, is achieved. The initial pheromone intensity is initialized to a value of 100 [39].

$$\mu_t = 0.1 \cdot \mu_{t-1} \tag{8}$$

$$\mu_t = \mu_{t-1} + 0.01 \cdot f\left(w_{t-1}^{\text{best}}\right). \tag{9}$$

4.2.2. Firefly algorithm

The firefly algorithm is a nature-inspired optimization technique that draws its inspiration from the flashing behaviours of fireflies. Developed by Xin-She Yang in 2008, this algorithm is categorized as a swarm intelligence method and is designed for tackling optimization challenges [40].

The firefly algorithm mimics the social behaviour of fireflies that use their flashing patterns to attract and communicate with other fireflies. The algorithm starts with an initial population of fireflies, each representing a potential solution to the optimization problem. The brightness of each firefly corresponds to its fitness value, with brighter fireflies being more optimal.

The algorithm uses the following steps to update the position of each firefly:

1. Evaluate the fitness of each firefly based on its brightness;
2. Move each firefly towards the brighter fireflies while also introducing some randomness to prevent premature convergence;
3. Repeat steps 1 and 2 until a stopping criterion is met.

The attractiveness of a firefly is determined by its brightness and distance from the other fireflies. The closer a firefly is to a brighter firefly, the more attractive it becomes and the more it will move towards that firefly. The firefly algorithm can be formulated as illustrated in Algorithm 2.

The population of fireflies is initiated through the 'InitializeFA' function, commonly executed with randomization. The firefly search procedure occurs within the while loop (lines 3–10 in Algorithm 2), comprising the following steps:

(a) The 'AlphaNew' function, an optional element in the firefly algorithm, adjusts the initial value of parameter α
(b) The 'EvaluateFA' function assesses solution quality. It includes the implementation of the fitness function $f(s)$.
(c) The 'OrderFA' function arranges the firefly population based on their fitness values.
(d) The 'FindTheBestFA' function selects the most optimal individual from the population [40].
(e) The 'MoveFA' function facilitates the repositioning of fireflies within the search space. Importantly, fireflies gravitate towards more appealing individuals. The firefly search procedure adheres to the maximum number of fitness function evaluations, MAX_FES.

In essence, each FA implementation can oscillate between these two asymptotic behaviors. The parameter range for the firefly algorithm in this study is outlined in Table 2. The coefficients of the algorithm were obtained empirically through PDP (Partial Dependence Plots) tests.

4.2.3. Hybrid of the ACO and the firefly algorithms

The proposed hybrid feature selection algorithm combines the strengths of both the ant colony optimization and the firefly feature selection algorithms. This algorithm aims to optimize the feature selection process and improve the overall performance. The details of the proposed algorithm are outlined in algorithm 3.

The proposed algorithm operates through several sequential steps:

1. In the initial step, the parameters of the firefly algorithm are configured.
2. Moving on to the second step, the feature selection process commences utilizing the firefly algorithm.
3. Results obtained from this process are saved for later reference.

Algorithm 2. The firefly algorithm.

```
1: t = 0;s* = ∅;γ = 1.0;              //initialize: best solution, attractiveness
2: K^(0) = InitializeFA();            //initialize a population
3: while (t < MAX_FES) do
4:    α^(t) = AlphaNew();             // determine a new value of α
5:    EvaluateFA(K^(t), f(s));        // evaluate s according to f(s)
6:    OrderFA(K^(t), f(s));           // sort s according to f(s)
7:    s* = FindTheBestFA(K^(t), f(s)); // determine the best solution
8:    K^(t+1) = MoveFA(K^(t));        // vary the attractiveness accordingly
9:    t = t + 1;
10: end while
```

Table 2. Firefly parameter setting.

Parameter	Values
No. Selection	20
No. Fireflies	50
No. Iteration Max	100

Algorithm 3. The proposed algorithm.

Step 1:	Set parameter of firefly algorithm: Number of selection = 10 Number of fireflies = 50 Maximum iteration = 100
Step 2:	Start feature selection using firefly algorithm
Step 3:	Save firefly algorithm output in array
Step 4:	Set parameter of ant colony algorithm: Data validation = 10 Maximum iteration = 50
Step 5:	Start feature selection using ant colony algorithm
Step 6:	Save ant colony algorithm output in array

4. Subsequently, in step 4, the parameters required for the ACO algorithm are defined and set.
5. In step 5, feature selection is initiated using the ACO algorithm, and it is applied to the results previously obtained from the firefly algorithm.
6. Finally, the outcomes of the ACO algorithm are saved as the output of the proposed methodology. The selected features undergo further processing via the ACO algorithm.

The parameters of the algorithm were obtained through trial and error.

4.3. Classification algorithm

The utilized classification algorithms in this research are the DTree, the kNN, and the SVM algorithms. A concise description of each of the algorithms is provided below.

4.3.1. The SVM algorithm

The SVM is a powerful classification algorithm that establishes a correlation between input and output based on labeled instances. It aims to categorize inputs based on certain criteria. The SVM uses non-linear kernel functions to transform the original dataset into a higher-dimensional feature space. This enables it to perform more complex classification tasks and achieve better results [41].

4.3.2. The kNN algorithm

The kNN algorithm is a commonly used and straightforward algorithm in machine learning, especially in tasks such as image classification. It is a supervised classification algorithm that selects the k-nearest neighbours of a given point using distance metrics, such as the Euclidean distance. To classify an unlabelled instance, the algorithm calculates the distance between the unlabelled instance and labelled instances and selects its k-nearest neighbours with their corresponding labels. The unlabelled instance is then classified by using either a weighted majority or a majority voting rule based on the labels of its k-nearest neighbours [42].

4.3.3. The DTree algorithm

The decision tree algorithm is a widely employed technique in machine learning. It constructs a model resembling a tree, illustrating decisions and their potential outcomes. This algorithm engages in recursive partitioning of the dataset into smaller subsets, determined by the input feature values. The objective is to optimize the homogeneity of these subsets. In this process, internal nodes signify features, while leaf nodes stand for class labels or decisions.

The construction of the tree follows a top-down, greedy approach. At each stage, the algorithm selects the most suitable feature for data division, grounded in an impurity measure like entropy or the Gini index. Decision trees are versatile, capable of handling both categorical and numerical data. Moreover, they are applicable to both classification and regression tasks [43].

5. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed method is implemented using MATLAB 2019a and evaluated using the DMR.

5.1. Classification evaluation without feature selection phase

This section presents the results of the classification experiment without feature selection on the DMR dataset using DTree, SVM, and kNN classifiers. The performance of each classifier is evaluated in terms of accuracy, specificity, and sensitivity, and the results are shown in Figure 5. This algorithm executed in 3.568975 seconds.

Based on the results obtained without feature selection, the DTree algorithm outperformed SVM and kNN classifiers in terms of accuracy, sensitivity, and specificity. This indicates that the decision tree model is a good fit for the DMR dataset and can accurately classify instances.

5.2. Classification evaluation with feature selection phase

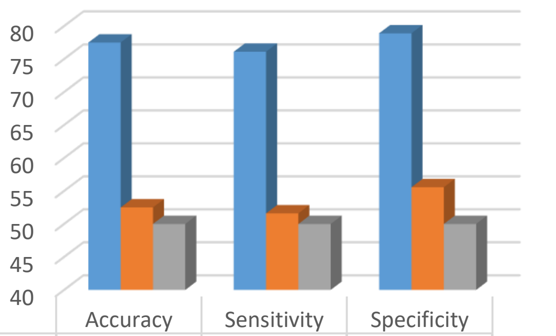
In this section, we performed classification using the ant colony and the hybrid of the ant colony and the firefly feature selection algorithms. The results of the experiments are depicted in Figure 6 and Figure 7. This algorithm executed in 4.464175 seconds.

Based on the experimental findings utilizing the ant colony feature selection algorithm, it is evident that the SVM classification algorithm demonstrates superior performance in terms of sensitivity and accuracy.

Based on the experimental results obtained from the hybrid of the ACO and the firefly feature selection algorithms, it is observed that the SVM classification algorithm exhibits superior performance in terms of sensitivity and accuracy. The firefly algorithm has strong capabilities in the exploration of the search space and can effectively move from local regions to better areas.

In contrast, the ACO algorithm excels at exploitation, leveraging its pheromone memory to reinforce successful solutions.

By combining these two algorithms, a balance between "exploration" and "exploitation" is achieved, something that individual algorithms might struggle to accomplish effectively on their own.



	Accuracy	Sensitivity	Specificity
DTree	77.5	76.1	78.9
SVM	52.5	51.6	55.56
kNN	50	50	50

Figure 5. The results without feature selection.

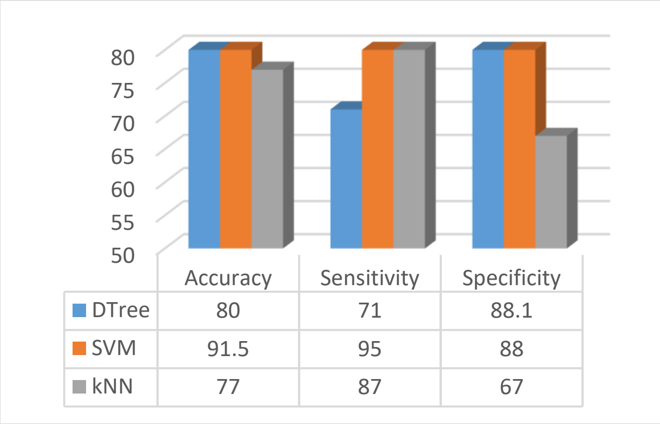


Figure 6. The experimental results using the ant colony feature selection algorithm.

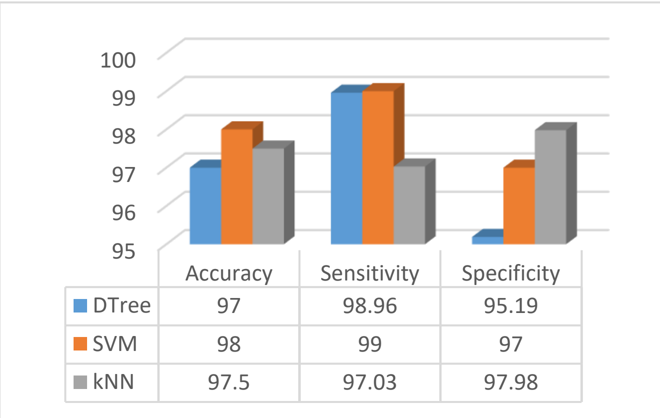


Figure 7. The experimental results using the hybrid of the ant colony and the firefly feature selection algorithms.

6. COMPARATIVE ANALYSIS

In this section, we conduct a comprehensive discussion on the comparison results of the performance evaluation metrics, based on the experiments conducted in the previous section. The experimental results, illustrating the performance of various classification algorithms, are presented in Figure 8.

Based on the data depicted in Figure 8, the highest achieved accuracy rate is 98 %, the sensitivity rate is 99 %, and the specificity rate is 97.98 %. These results indicate the overall effectiveness of the classification algorithms using the ant colony-based feature selection algorithm. Table 3 summarizes the results for a more detailed comparative analysis. Table 4 provides a summary of the experimental outcomes, presenting accuracy, specificity, and sensitivity metrics in comparison to other CAD systems.

As shown in the summary table, most previous works have utilized the DMR dataset, highlighting its prominence and reliability for benchmarking in this field. Studies such as [19] and [23] employed optimization algorithms including Dragonfly, ACO, and PSO for feature selection, combined with SVM classifiers. These approaches yielded accuracies of 97 % and 97.4 %, respectively. Similarly, study [25] applied ACO on the ELVIRA dataset, achieving an accuracy of 95 %.

In [26], which used the WBCD dataset, a hybrid approach combining an artificial immune system and ABC algorithm with an ANN classifier resulted in the highest reported accuracy of 99.11 %. However, direct comparison with other studies is limited due to dataset differences.

Study [13] utilized the Gray Level Run Length Matrix (GLRLM) for feature extraction and a kNN classifier, reporting an accuracy of 95.45 % alongside sensitivity of 99.17 % and specificity of 88.07 %. These results indicate strong detection capability (high sensitivity) but relatively lower specificity, suggesting a higher false-positive rate.

The approach proposed in this research introduces a hybrid feature selection method combining the ant colony and the firefly algorithms, evaluated using DTree, SVM, and kNN classifiers. The highest accuracy was obtained using SVM at 98 %, surpassing most previous studies on the DMR dataset. Moreover, specificity and sensitivity values of 97 % and 99 %, respectively, demonstrate a well-balanced performance in both correctly identifying positive cases and minimizing false positives.

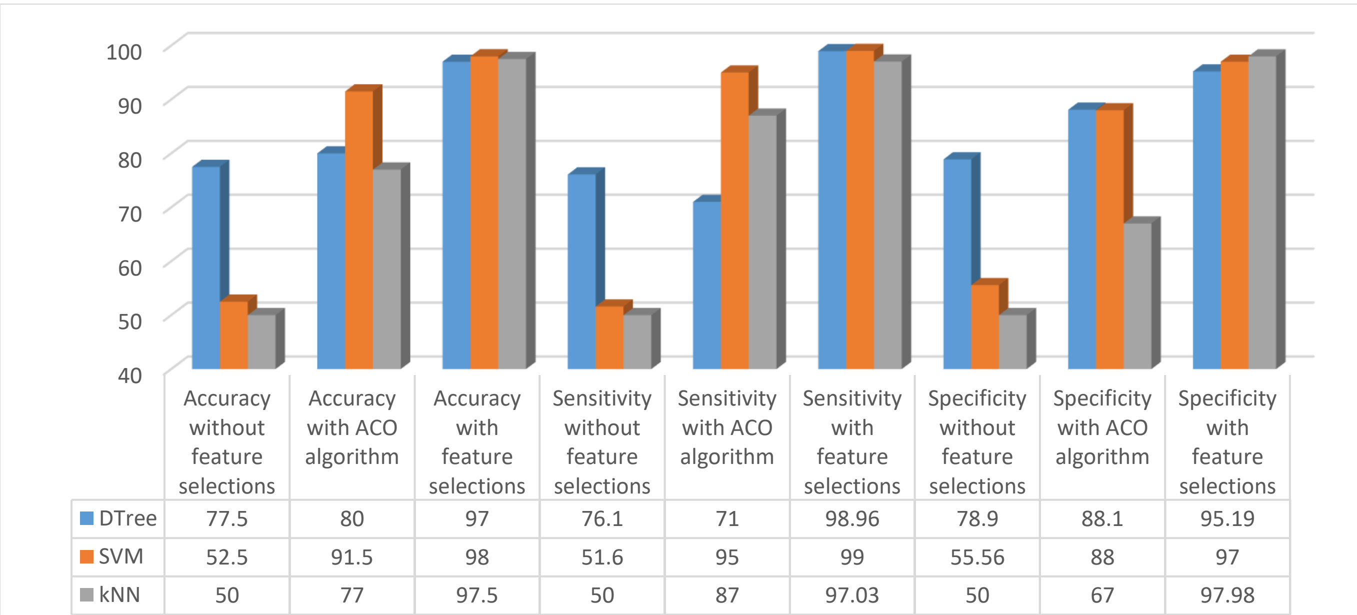


Figure 8. The experimental results of classifications.

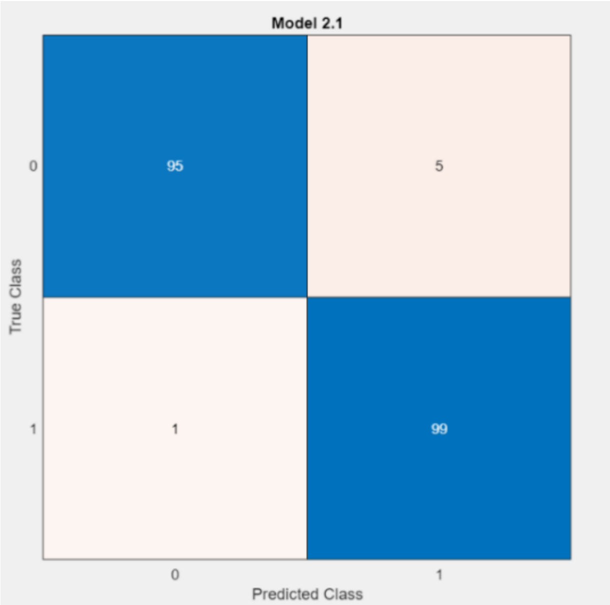


Figure 9. The confusion matrix image of the DTree.

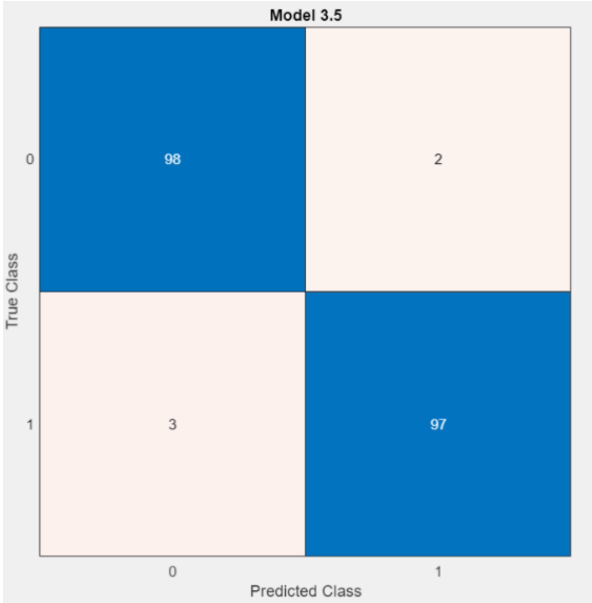


Figure 10. The confusion matrix image of the kNN.

In summary, the proposed hybrid optimization-based feature selection significantly improves classification performance, indicating the effectiveness of combining swarm intelligence algorithms in enhancing the discriminative power of the selected features.

7. CONCLUSION

Thermography, with features such as non-invasiveness, painlessness, cost-effectiveness, and the potential to provide significant treatment opportunities for patients, has been

Table 3. Performance of classifiers.

Evaluation metrics	Classifiers					
	DTree		SVM		kNN	
	Without feature selection	With hybrid of ant colony and firefly	Without feature selection	With hybrid of ant colony and firefly	Without feature selection	With hybrid of ant colony and firefly
Accuracy (%)	77.5	97	52.5	98	50	97.5
Sensitivity (%)	76.1	98.96	51.6	99	50	97.03
Specificity (%)	78.9	95.19	55.56	97	50	97.97

Table 4. Results comparison.

Reference	Year	Database	Feature selection method	Classifier	Classifier & performance rate (%)
[19]	2022	DMR	Grunwald-Letnikov-aided Dragonfly	SVM	Accuracy = 97 %
[23]	2023	DMR	ACO and PSO	SVM	Accuracy = 97.4 %
[25]	2021	ELVIRA	ACO	SVM	Accuracy = 95 %
[26]	2021	WBCD	Integrated artificial immune system and ABC	ANN	Accuracy = 99.11 %
[13]	2021	DMR	GLRLM	kNN	Accuracy = 95.45 % Specificity = 88.07 % Sensitivity = 99.17 %
[28]	2021	DMR	BPSO	SVM	Accuracy = 96.22 %
[29]	2021	DMR	GA	SVM	Accuracy = 95 % Specificity = 95 % Sensitivity = 95 %
[14]	2021	DMR	mRMR, GA and RSFS		Accuracy = 79.31 % Specificity = 75 % Sensitivity = 83.36 %
This article	2026	DMR	hybrid of ant colony and firefly	DTree	Accuracy = 97 % Specificity = 95.19 % Sensitivity = 98.96 %
				SVM	Accuracy = 98 % Specificity = 97 % Sensitivity = 99 %
				kNN	Accuracy = 97.5 % Specificity = 97.98 % Sensitivity = 97.03 %

recognized as a preferred technique for detecting breast cancer. This article introduces an innovative method aimed at enhancing the accuracy of breast cancer detection by utilizing infrared thermal images. Within this framework, a hybrid feature selection algorithm is employed, combining the ant colony algorithm with the firefly algorithm. The ant colony algorithm has demonstrated significant efficacy in selecting the best features for reducing the complexity of the diagnostic process. The ACO, with the collective behaviour of ants, excels in optimizing complex and large-scale problems, while the firefly algorithm, with its attraction mechanism, is effective for global search and multi-objective optimization. The evaluation results indicate that the hybrid feature selection algorithm achieves an average accuracy of 98 %, a specificity of 97 %, and a sensitivity of 99 %. Comparative analysis highlights the advantages of the proposed algorithm compared to other existing feature selection algorithms. The authors intend to use deep learning-based algorithms and increase the number of images to improve detection performance in future studies.

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