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Integrated Bee Colony and Tabu Search Optimization for Feature Selection and Classification of Breast Cancer in Digital Mammogram Images

J. Nithya and M. Mugilya

Department of IT, K.S.R. College of Technology, Tamil Nadu, India

Abstract: Digital mammography is a superior form of mammography which uses digital receptors and computers rather than using x-ray film to examine breast tissue for breast cancer. It is "spot view" for breast biopsy and "full field" for screening. Cuckoo search performs the local search more effectively and there remains only single parameter away from the population size. It reduces the make span and the scheduling to be used in high power and scientific computing. A Breast biopsy is performed by different modality like ultrasound or magnetic resonance imaging (MRI). Digital spot view mammography provides faster and accurate stereotactic biopsy since the patient time remains much shorter by analyzing and improving time and patient comfort respectively. The existing system presented a hybrid Ant-Cuckoo Colony Optimization algorithm for efficient feature selection to detect breast cancer in Digital Mammogram. Support Vector Machine classifier with Radial Basis Kernal Function is used to determine normal and abnormal mammogram. It helps to provide better classification rate and accuracy. However, the method is unable to provide combinatorial optimization for best feature selection. And also, it failed to implement memory structure to reduced information share rate. Feature correlation was not specified poor relativity of malignant and benign cancer detection. Therefore to overcome these drawbacks, the proposed work presents an ant cuckoo colony optimization for feature selection in the digital mammogram. It developed a Bee Colony Tabu Search Optimization technique for feature selection and classification of normal, abnormal and critical breast cancer detection from Digital mammogram images. The Performance measure of the proposed ant-cuckoo colony optimization for feature selection in a digital mammogram are done with the following metrics like local and global maxima of extracted features, correlation coefficient of features (selection), best feature selection rate, a number of classes, classification accuracy and breast cancer detection rate.

Key words: Stereotactic biopsy · Breast cancer · Digital mammography · Tabu Search Optimization

INTRODUCTION

A mammogram is the most common screening method which uses X-rays to scan the breasts. The images are analyzed for an irregular appearance and so the doctor analyzes for any changes from previous tests. This method of achieving the mammogram images is similar for both types. A technician positions the breast between two plates, flattens and compresses it by taking images of the breast from top to bottom and side to side. Film mammograms are recorded on hard files. X-rays are changed to the electric signals to be stored in a computer with the digital kind. Detection of masses in digital mammograms helps in an early diagnosis of breast cancer. An automated segmentation of a region of interests is done by 8-bit quantization method. Gray Level Co-occurrence Matrices at four directions is developed for every ROI because that the Gray Level Co-occurrence Matrices gives the texture-context information. The most widely used technology for earlier detection of breast cancer is the digital mammogram. The detecting elements like masses and lesions in the digital mammograms are noisy and possess low contrast. The objective of the method is to increase the mammogram images by reducing the noise using a median filter, image sharpening and image smoothing. The features extracted from those images of the database are used to train up the neural networks for classification. The algorithm is used on the digital mammograms by the Mammogram Image Analysis database. The experimental results prove that the breast region obtained by the algorithm follows as extracted by an expert radiologist.

Corresponding Author: J. Nithya, Department of IT, K.S.R. College of Technology, Tamil Nadu, India.

Literature Survey: The author described about Bee Colony Algorithm for Neighborhood Search in Job Shop Scheduling Problem and population-based approach applies to honey bees foraging model for solving job shop scheduling problems. The algorithm poses an efficient neighborhood structure to search feasible solution. The initial solutions are developed by a set of priority dispatching rules. Experimental results are compared with the proposed method honey bee colony and the existing method ant colony, tabu search and shifting bottleneck procedure on a set of job shop problems [1]. The author presented an algorithm for feature Selection by feature selection in small sample size situations. By applying feature selection method, it gives the results of the classification of SAR satellite images by four various types of texture models. Pooling features extracted from different texture models by a feature selection shows substantial development in the classification accuracy. The method uses feature selection for classifying hand printed characters which derive the value of feature selection to reduce the number of features need by classifier design [2]. The author elaborated the Feature Selection Algorithms by assessing the performance in a controlled scenario. It measures the algorithms by taking the amount of relevance in the account and by taking irrelevance and redundancy on sample data sets. The measure evaluates the degree of match in the output provided by the algorithm and the optimal solution. It studies about sample size effects also [3]. The author explained about the fundamental concepts of Tabu Search in a tutorial fashion. Some emphasis shows the relationships with classical Local Search methods on the elements of TS heuristic such as the definition of the search space, the neighborhood structure and the search memory. Various sections explain main concepts like search intensification and diversification to provide references and related work on TS. Recent advances [4]. The author briefed about Feature Selection for Classification to find four steps of a complicated feature selection method for categorizing the different methods in generation rocedures and evaluation functions. It exposes hitherto unattempted generation procedures and evaluation functions. Representative methods are selected from every category to provide an explanation and discussion [5].

The author presented a user's guide tabu search to emphasize a method for helping a user understanding the basic principles. Recent developments and extensions contributed to increase the effectiveness of the method. The important aspects of tabu search are the capability to adapt a rudimentary prototype implementation for encompassing extra elements like constraints and objective functions [6]. The author developed a Bee Colony Optimization to perform difficult tasks by dynamically interacting with each other. The artificial bee colony is partially alike and different from bee colonies in nature. The BCO can solve deterministic combinational problems and also the combinational problems characterized by uncertainty [7]. To solve Engineering Design Problems, Adaptive Bee Colony in an Artificial Bee Colony is presented to develop the population of food sources significantly and the variant is named as A-ABC. A-ABC is developed for improving convergence speed and exploitation capability to employ the concept of elitism and the bees towards the best food source is called E-ABC [8]. The author proposed the Efficiency of Artificial Bee Colony and the Firefly Algorithm in Solving the Continuous Optimization Problem to present the efficiency of the algorithm. It analyzes the continuous optimization problems of the vast limit answer and the close optimized points are tested. ABC algorithm and FA are developed to solve the continuous optimization problems from the accuracy to reach the optimized solution and also the optimized time and reliability [9]. Briefed Comprehensive review of Artificial Bee Colony Algorithm. ABC algorithm is easy and more flexible when compared to swarm-based algorithms. This method is the most popular and widely used due to the good convergence properties. ABC algorithms enhance the foraging behavior of honey bees to solve optimization, unconstrained and constrained problems [10].

The author studied about the Applications Survey on Bee Colony Optimization. Swarm Intelligence is so commonly analyzed by many based on the study of actions of individuals in the different decentralized system. It was developed to solve various optimization problems in different areas. The benchmark system BCO provides the team work and so used in different optimization problem [11]. Breast Cancer Detection Using Image Processing Techniques in proposed system develop the use of segmentation with fuzzy models and classification by the crisp k-nearest neighbor (k-NN) algorithm to assist the breast cancer detection in digital mammograms. This method uses images from the Digital Database for Screening Mammography. It improves segmentation by adding window means and standard deviations produced by the k-NN rule [12]. The author designed Mammogram of Breast Cancer Detection Based using Image Enhancement Algorithm create a multitude of options to improve the visual quality of images. A frequency domain smoothing-sharpening method is developed to beneficially increase mammogram images. This method provides the merits of enhancing and sharpening process to highlight changes in the image intensity. It improved results for denser mammographic images by selecting the parameters almost invariant and severity of the abnormality provides significantly improved results for denser mammographic images [13]. Fast Hybrid PSO and Tabu Search Approach for Optimization of a Fuzzy Controller are optimized by hybrid Particle Swarm Optimization (PSO) and Tabu Search (TS) method. The algorithm automatically maintains the membership functions of fuzzy controller inputs and the fuzzy rules conclusions. The author measures the best solution for each PSO iteration and found the best neighbor by Tabu search. It reduces the number of iterations and computation time to maintain the accuracy and response time [14]. Tabu Search Fundamentals and Uses achieved widespread successes to evolve the practical optimization problems. Applications are developed in many areas like resource management, process design, logistics, technology planning and general combinatorial optimization. Hybrids procedures, both heuristic and algorithmic produced significant results. The practical achievements of tabu search produced good research to exploit its underlying ideas effectively [15].

An Overview of Bee Colony: In Bee Colony, a population-based algorithm, the position of a food source is represented as a possible solution for optimization problem in which the food source nectar amount is corresponds to the quality (fitness) of the associated solution. Number of the employed bees and the solutions obtained in the population are equal. First an initial population is randomly generated. After initialization, the population is subjected to repeat the cycles of the search processes of the employed, onlooker and scout bees, respectively. An employed bee modifies a source position by discovering a new food source position and saved in its memory. If the nector amount has higher count than previous then it remember the new one by forgetting the old position else the initial position is stored in memory. Once search process is completed by all the employed bees the position of the food source are shared with onlooker bees in dance area. The nectar informations are evaluated by each onlooker bees and food sources are chosen. Once chosen the food, the modifications of positions and nector amounts are checked in memory. Providing that its nectar is higher than that of the previous one, the bee memorizes the new position and forgets the old one. The sources abandoned are determined and new sources are randomly produced to be replaced with the abandoned ones by artificial scouts.

Application: The application of Bees Algorithm has found in engineering field such as:

Optimization of classifiers/clustering systems

- Manufacturing
- Control
- Bioengineering
- Other optimization problems
- Multi-objective optimization

Bee Algorithm

- For an optimization problem, the Bees Algorithm mimics the foraging strategy of honey bees to look for the best solution. Each candidate solution inlcudes a food source (flower) and a population (colony) of n agents (bees) for searching the solution space. An artificial bee visits every time a flower (lands on a solution) and evaluates its profitability (fitness). An initialization procedure and the main search cycle is present in a bee algorithm which is iterated for a given number T of times, or until a solution of acceptable fitness is found. Each search cycle is composed of five procedures: recruitment, local search, neighborhood shrinking, site abandonment and global search.

The pseudocode for the standard Bees Algorithm [2]

```
1 for i=1, …, ns
 i. scout[i]=Initialise_scout()
 ii. flower_patch[i]=Initialise_flower_patch(scout[i])
2 do until stopping_condition=TRUE
 i Recruitment()
 ii for i =1, …, nb
flower_patch[i]=Local_search(flower_patch[i])
```

flower_patch[i]=Site_abandonment(flower_patch[i])
flower_patch[i]=Neighbourhood_shrinking(flower_patch[i])
iii for i = nb, …, ns
flower_patch[i] = Global_search(flower_patch[i])}

In the initialization routine ns scout bees are randomly placed in the search space and evaluate the fitness of the solutions where they land. For each solution, a neighborhood is delimited. Scouts visited the nb=ns in the recruitment procedure then fittest solutions (best sites) perform the waggle dance. They recruit further foragers to search the neighborhoods of the most promising solutions. The scouts that located the very best *ne*=*nb* solutions (elite sites) recruit *nre* foragers each, whilst the remaining *nb*-*ne* scouts recruit *nrb*=*nre* foragers each. Thus, the number of foragers recruited depends on the profitability of the food source.

In the local search procedure, the recruited foragers are randomly scattered within the flower patches enclosing the solutions visited by the scouts (local exploitation). If any of the foragers in a flower patch lands on a solution of higher fitness than the solution visited by the scout, that forager becomes the new scout. If no forager finds a solution of higher fitness, the size of the flower patch is shrunk (neighborhood shrinking procedure). Usually, flower patches are initially defined over a large area and their size is gradually shrunk by the neighborhood shrinking procedure. Scope of the local exploration is focused immediately on the area close to the local fitness best. If no improvement in fitness is recorded in a given flower patch for a pre-set number of search cycles, the local maximum of fitness is considered found, the patch is abandoned and a new scout is generated randomly. A small number of scouts explores the solution space looking for new regions of high fitness. The global search procedure re-initializes the last ns-nb flower patches with randomly generated solutions. At the end of one search cycle, the scout population is again composed of *ns* scouts: *nr* scouts produced by the local search procedure and *ns*-*nb* scouts generated by the global search procedure. The total artificial bee colony size is *n*=*ne*•*nre*+(*nb*-*ne*)•*nrb*+*ns* (elite sites foragers + remaining best sites foragers + scouts) bees.

An Overview of Tabu Search: For a past fifteen years, over hundreds of papers were presenting on Tabu Search (TS). TS is a heuristic method originally proposed by Glover in 1986, to various combinatorial problems. In most of the case, the methods described provides a solutions for optimality and to tackle the difficult problems at hand. The success made most of people to find a good solutions for huge combinatoral problem. Many have survey on limitations and techniques used. This paper addresses the situation which provides an introduction in tutorial form which focused on the basics of TS. Two different concepts such as the Classical Vehicle Routing Problem (CVRP) and the Capacitated Plant Location Problem (CPLP) are discussed. These will be introduced in the following section. The remainder section of the paper is organized as follows by including the basic concepts of TS like search space, neighborhoods and short-term tabu lists are illustrated in Section 2. Concepts that are intermediate, yet critical, like intensification and diversification, are described in Section 3. Section 4 briefly discussed on advanced topics and recent trends in TS. Section 5 short list of key references on TS and its applications. The practical tips for newcomers are detailed in section 6. Finally section 7 concludes the paper with some general advice on the application of TS to combinatorial problems.

Feature Selection Of Bee Colony And Tabu Search Optimization In Digital Mammogram: Tabu search is local (neighborhood) search creates a potential solution for identifying best feature selection to check its immediate neighbor's correlated feature and to find an improved solution. Cuckoo local search get stuck in suboptimal regions or on plateaus where there are many solutions fitted equally. Tabu search increases the performance of local search by freeing certain basic rule with a correlation coefficient of the related feature. Firstly, worsening moves are accepted at each when no improving move is present and when the search is captured at a strict local minimum. Secondly, prohibitions are developed to discourage search by coming back to the visited solutions. Then the development of tabu search uses memory structures to describe the visited solutions or user-provided sets of rules for feature selection.

Tabu search algorithm does not use possible for improving the classification accuracy to discriminate between normal, abnormal and critical feature values for breast cancer detection. The method provides combinatorial optimization and continuous optimization for obtaining the best feature selection. BCO and Tabu search integration enhance the feature selection rate.

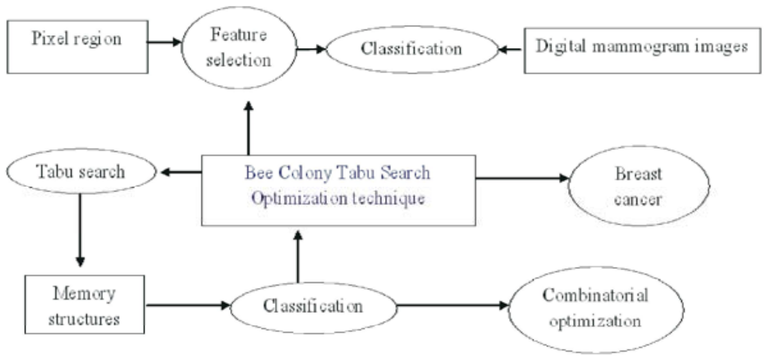

Fig. 3.1: Architecture Diagram of ant cuckoo colony optimization for feature selection in digital mammogram

MATERIALS AND METHODS

It consists of the following modules. They are

- Feature extraction on Digital Mammogram Images
- Feature Selection with Bee Colony Optimization
- Feature Classification based on Tabu Search
- Detection of Breast Cancer
- Performance Evaluation

Feature Extraction on Digital Mammogram Images: `Feature extraction of digital mammogram images is done with multi-scale texture features of the pixel regions surrounding micro-calcification. The Region of interest for the image is analyzed with its texture feature values. A different set of text feature is extracted on ROI. Extracted feature sets are analyzed for evaluating discriminating malignant by benign tissue.

High pixel intensity value in mammogram image is chosen compared to neighboring pixels. Comparative analysis continues till discriminate intensity value of neighboring pixel is arrived region of interest is obtained by grouping homogenetic intensity pixels. Mammogram images quality is improved by reducing noise using a median filter, image sharpening and image smoothing. The Region of interest based on intensity and texture values are analyzed with gradient and geometrical features. Features extracted from the mammogram images are finally fed to feature selection stage.

Feature Selection with Bee Colony Optimization: Feature selection is done based on features extracted from the mammogram images. Bee Colony Optimization (BCO) is applied for selecting the features used for classification of breast cancer identification. BCO approach performs searching of features extracted by combining global and local search on the region of interest in the mammogram image does combinatorial optimization and continuous optimization.

The Correlation coefficient is evaluated with combinatorial optimization of local search. Continuous optimization search is done on all the ROI regions of the mammogram images. Best features are selected with correlated coefficient in both local and global search. Best selected features provide an effective classification of different stages of breast cancer detection. Feature selection of extracted features from mammogram images is stored in pixel vectors. Feature subset is generated based on a global and local search of Bee on pixel vector of correlated features. Feature subset generated is assessed as selected features of ROI.

Feature Classification Based on Tabu Search: Feature classification is done on selected feature using Tabu search mechanism. Tabu search does efficient local, i.e., neighborhood search on the ROI provide a potential solution to identifying best feature rich classes for detection of various stages of breast cancer features.

Tabu search improve classification process by reducing basic rule corresponding to correlated feature for demarcating features values at different stages of breast cancer. In tabu search on selected features worst case features are initially accepted on a continuous search for best fitness value. Feature set is correlated with different stages of breast cancer detection class at a strict local minimum. Prohibitions (so called Tabu) are introduced to discourage search on worst case features in later iteration for previously-visited solutions

Detection of Breast Cancer: Detection of breast Cancer is done with training classes generated and test data by evaluating the accuracy of matching features classes between trained class and test class data. Detection efficiency is measured by the pattern classifier using hyperplane to separate two classes of patterns based trained and test classes with selected feature values. Evaluate a class index by taking value 1 or 0. Tabu search classifies binary classes by finding and using a class boundary in the hyper plane maximizing margin in given training data. The training data samples along hyperplanes near class boundary are evaluated margin is distance between similarity feature values and class boundary hyperplanes determine the detection accuracy of breast cancer.

Performance Evaluation: Performance evaluation of proposed work is done with following parameters Local and Global Maxima of extracted features, Correlation Coefficient of Features (Selection), Best feature selection rate, Number of classes, Classification accuracy, Breast Cancer Detection Rate.

Performance Metrics: In this section evaluate the performance of ant-cuckoo colony optimization for feature selection through a Matlab environment. One of the major contributions of this work is it detects breast cancer in Digital Mammogram. The performance metrics of the parameters is Local and Global Maxima of extracted features, Correlation Coefficient of Features (Selection), Best feature selection rate, Number of classes, Classification accuracy and Breast Cancer Detection Rate.

The performance metrics are is

- Local and Global Maxima of extracted features
- Classification accuracy
- Breast Cancer Detection Rate

Local and Global Maxima of Extracted Features: Local and Global Maxima of extracted features makes the local geometry of the dataset through dividing the data set into four domains. The Combination of local and global features is useful where segmentations of breast cancer are predicted. Firstly, it uses a "stacking" ensemble method and then secondly it uses a hierarchical classification system. Results show the extraordinary performance by using this method with a high reduction rate on a challenging digital mammogram application.

Table 4.1: Number of classes Vs Local and Global Maxima of extracted features (%)

	Local and Global Maxima of extracted features (%)	
Number of classes	Existing ACO	Proposed BCO
10	46	53
20	48	58
30	51	65
40	54	72
50	66	76

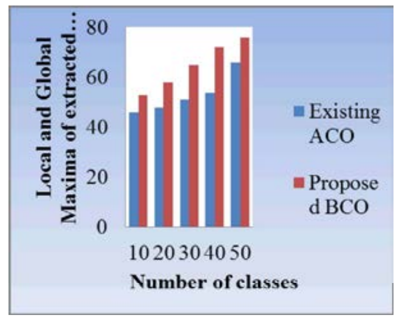

Fig. 4.1: Number of classes Vs Local and Global Maxima of extracted features (%)

Fig. 4.1 demonstrates the Local and Global Maxima of extracted features. X axis represents the Number of classes whereas Y axis denotes the Local and Global Maxima of extracted features using both the Ant-Cuckoo Colony Optimization (ACO) technique and the proposed Bee Colony Tabu Search Optimization (BCO) technique. When the number of classes is increased, Local and Global Maxima of extracted features get increased consequently. The Local and Global Maxima of extracted features are illustrated using the existing ACO and proposed BCO Technique. Figure 4.1.shows the better performance of Proposed BCO method than existing ACO and proposed BCO. The ant-cuckoo colony optimization for feature selection in digital mammogram achieves 10 to 15% high performance when compared with the existing system.

Classification Accuracy: The classification accuracy in the breast cancer on the training and test data are evaluated. It refers to the ability of the mammogram to detect correctly cancer by using the previously collected data. Therefore, Classification accuracy in a digital mammogram is the number of images properly classified divided by the total number of images provided during experimentation, multiplied by 100 to turn it into a percentage.

Table 4.2: Number of classes Vs Classification accuracy (%)

	Classification accuracy (%)	
Number of classes	Existing ACO	Proposed BCO
10	48	70
20	52	72
30	58	78
40	61	84
50	69	87

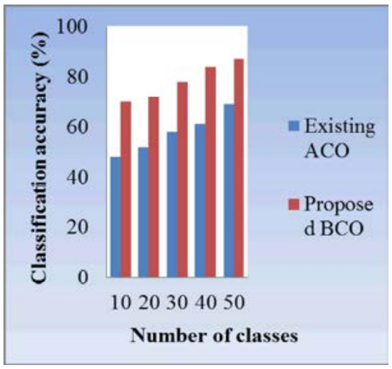

Fig. 4.2: Number of classes Vs Classification accuracy (%)

Fig 4.2 demonstrates the classification accuracy. X axis represents the Number of classes whereas Y axis denotes the classification accuracy using both the Ant-Cuckoo Colony Optimization (ACO) technique and the proposed Bee Colony Tabu Search Optimization (BCO) technique. When the number of classes is increased, classification accuracy gets increased consequently. The classification accuracy is illustrated using the existing ACO and proposed BCO Technique. Figure 4.2 showed the better performance of Proposed BCO method than existing ACO and proposed BCO. The ant-cuckoo colony optimization for feature selection in digital mammogram achieves 15 to 20% high performance when compared with the existing system.

Breast Cancer Detection Rate: Breast cancer detection rate on different classes are obtained. The regions of interest are considered as the classes (i.e. input) for measuring the detection rate. With the increase in the classes, the detection rate is also increased, though efficiency proved to be higher in a comparative manner using the digital mammogram.

Fig 4.3 demonstrates the Breast Cancer Detection Rate. X axis represents the Number of classes whereas Y axis denotes the Breast Cancer Detection Rate using both the Ant-Cuckoo Colony Optimization (ACO) technique and the proposed Bee Colony Tabu Search Optimization (BCO) technique. When the number of classes is increased, Breast Cancer Detection Rate gets increased consequently. The Breast Cancer Detection Rate is illustrated using the existing ACO and proposed BCO Technique. Figure 4.3 showed the better performance of Proposed BCO method than existing ACO and proposed BCO. The ant-cuckoo colony optimization for feature selection in digital mammogram achieves 18 to 23% high performance when compared with the existing system.

Table 4.3: Number of classes Vs Breast Cancer Detection Rate (%)

	Breast Cancer Detection Rate (%)	
Number of classes	Existing ACO	Proposed BCO
10	19	26
20	21	29
30	22	32
40	24	36
50	26	39

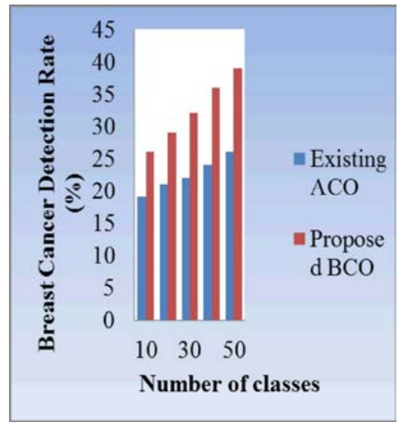

Fig. 4.3: Number of classes Vs Breast Cancer Detection Rate (%)

CONCLUSION

This paper proposes a Bee Colony Tabu Search Optimization technique for feature selection and classification of normal, abnormal and critical breast cancer detection from Digital mammogram images. Bee colony optimization work by nature inspired bee collecting honey from flowers. Best feature selection is effectively arrived with BCO to detect the breast cancer. Tabu search enhances the performance of local search by relaxing its basic rule corresponding to a correlation coefficient of a related feature. In future work to extend the process of tabu search technique and extraction process will be improved and upgraded.

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