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Breast Cancer Classification Framework Using Dolphin Echolocation Algorithm

نموذج لتحسين تصنيف مرض سرطان الثدي بواسطة اختيار الخواص الفعالة باستعمال خوارزمية الدلافين لتحديد المواقع بالصدى

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Abstract— the most doctors spend a lot of time for detecting a benign tissue which is easily be distinguished from malignant one in a computerized community. This denotes to a waste of time and resources that can be spent in classifying the difficult cases. As a result, many researchers began to develop diagnostic methods with aid of computer applications that uses image processing techniques. It helps to classify existence of diseases such as breast cancer where a lot of features are used to distinguish this disease. This paper employees a meta-heuristic algorithm (Dolphin Echolocation Algorithm DEA) to select the most effective features from all expensive used features to accurate and fast classification of breast cancer. In this research, Fine Needle Aspiration images are used. Additionally, three classifiers (SVM, BP-NN, and KNN) are utilized to classify medical data. For increasing the accuracy and reducing the time, many feature selection algorithms are used. The results show that meta-heuristic algorithms (GA and suggested DEA) are outperformed other feature selection methods.

Keywords—
Breast Cancer; Feature Selection; Feature extraction; Classification; FNA.

الملخص

اغلب الاطباء يقضون وقت طويل في تشخيص الحالات المرضية , وهذا يسبب ضياع الوقت والجهد التي يجب ان تستغل في تشخيص الحلات المرضية الصعبة فقط. النتيجة ان العديد من الباحثين بدءوا بتصميم انظمة حاسوبية لتشخيص الامراض بمساعدة تقنيات معالجة الصور, حيث هذه الانظمة تساعد في تحديد وجود المرض من عدمه مثل مرض سرطان الثدي باستعمال العديد من الخواص. هذا البحث وضف احد الطرق الحدسية (خوارزمية الدلافين لتحديد المواقع بالصدى) لاختيار الخواص الفعالة من بين جميع الخواص التي يتم استخراجها من الصور وهذا يسرع ويحسن من نتائج تصنيف الصور. استعملت في هذا البحث الصور النسيجية بالاضافة الى ذلك استعملت ثلاثة مصنفات لاختبار عملية التصنيف (SVM, BP-NN, KNN) وكذلك استعملت العديد من طرق اختيار الخواص. اظهرت النتائج بأن الطرق الحدسية (خوارزمية الدلافين والخوارزمية الجينية) حصلت على نتائج افضل من بقية طرق اختيار الخواص الاخرى.

1- Introduction

Breast cancer is considered as the most common cancer among women. In 2008, one million and a half women are diagnosed as breast cancer patients and half million women are dead by this disease around the world. For a long time, the researchers were trying to discover a successful a way to treat this deadly disease. An early diagnosis is the key for controlling on this malignant disease [1, 2].

A triple-test examination is one of the important tools for breast cancer diagnosis [14]. The triple-test examination contains: i) Self-examination of breast, ii) mammography imaging of breast, and iii) Fine Needle Biopsy (FNB) and Fine Needle Aspiration (FNA). The collected cells (by FNA or FNB) can be tested by microscope. This is to detect the presence of cancerous cells. The current detection method requires long-time experience of the cytologist that is responsible for the diagnosis.

In this research, a classification method is improved to distinguish between malignant cells and benign cells. This method depends on cytological FNA images, where FNA image of a patient is classified as benign or malignant. This is achieved by using three types of features. Benign nuclei are characterized by uniformity in appearance, whereas characteristics of cancerous nuclei are having irregular shapes. Morphological metric measures the size of cells, cell grouping and color changes of the nuclei [19].

Among these extracted features, feature selection method should be utilized to find the most discriminative features. A meta-heuristic, Dolphin Echolocation Algorithm, is proposed in this research for feature selection. Finally, three different classification methods were used for classifying whether the patient's FNA image is benign or malignant. These classifiers are Support Vector Machine (SVM), Back–Propagation Neural Network (BP-NN), and K-Nearest Neighbor (KNN). For breast cancer classification, some literatures can be found in [4,5,6,7,8,9,10,11,12,13,14,15,16].

The rest of paper contains four sections. In Section 2, some feature selection methods of medical data are explained. Section 3 illustrates the proposed classification method. In Section 4, the experiments' results are tabulated. Lastly, Section 5 concludes the paper.

2- Related Work

Feature selection (FS) methods are used for high-dimensional reduction of data and it is useful for machine learning and data mining problem [6]. FS methods remove irrelevant features from all extracted features. FS process has two phases: i) phase of searching, it searches in feature vector, and ii) phase of evaluation, it evaluates the searched features. Searching algorithms (of the first phase) consider one of the important keys of FS methods. Types of these algorithms include complete, heuristic features [3], and random search [7]. These algorithms aim to find the best features [10]. To do this, an exhaustive search must be applied, but in high dimensional data this will be impractical in FS.

An alternative approach, hill climbing, can be used. This approach speeds up the convergence process to the solution vector. However, there is a possible for converging to non-optimal set of features. Therefore, meta-heuristic search algorithms are used to find optimal set of features [11].

These nature-inspired algorithms such as genetic algorithms and particle swarm optimization are utilized with different fitness function. These meta-heuristic algorithms are usually used for optimization tasks. These algorithms can be used in feature selection process; but mapping concept from optimization into FS is required. The properties that make meta-heuristic algorithms suitable for FS can be found in [31].

3 – The Proposed Method:

In Figure 1, phases of the proposed medical classification model are depicted.

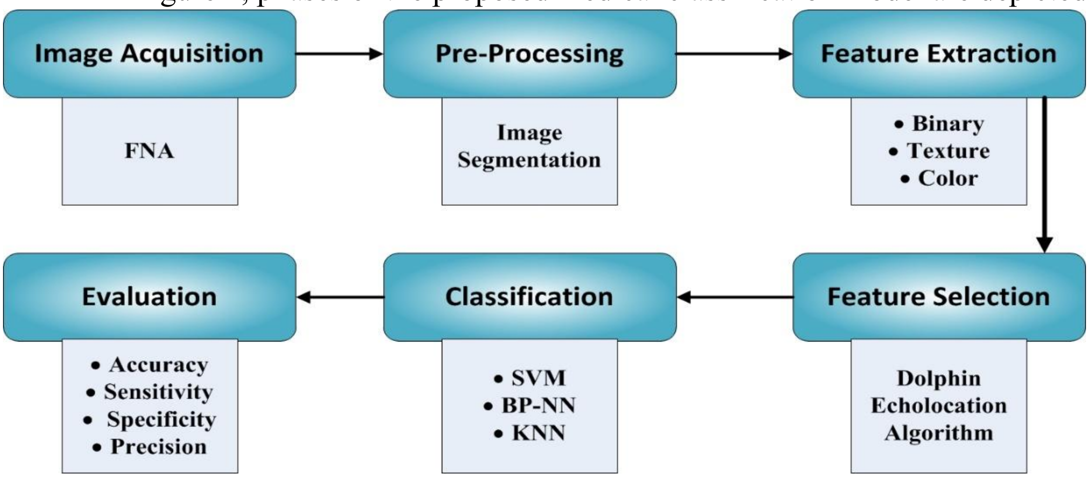


Figure 1: Phases of the Proposed Medical Classification Model

3.1 Image Acquisition

The process of obtaining the first phase of the proposed model is acquiring digital images, microscope images. There is a special camera to take pictures in optical microscope which is called Fine Needle Aspiration (FNA) images, as shown in Figure 2.

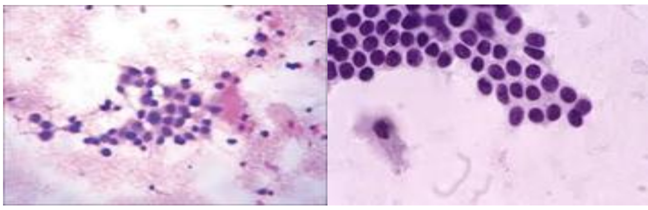
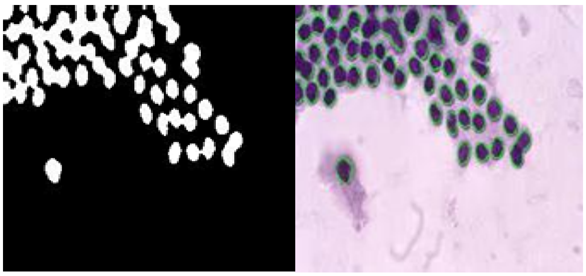


Figure 2: Microscope (FNA) images.

3.2 Image Pre-Processing

To decide the tumor is benign or malignant, nuclei of cells must be detected and isolated from background and from other objects on the image. This process is very important because all subsequent processes are depending on this segmentation process [20,21, 22, 23, 24].

Usually, this task can be achieved either automatically or semi-automatically, using well-known segmentation method [4, 5, 15, 16, 17, 18, 22]. However, precise segmentation is still a difficult task. In this research, the combination of the classical region growing technique with (clustering segmentation method) is achieved by using (Fuzzy C-mean) algorithm, as depicted in Figure 3.

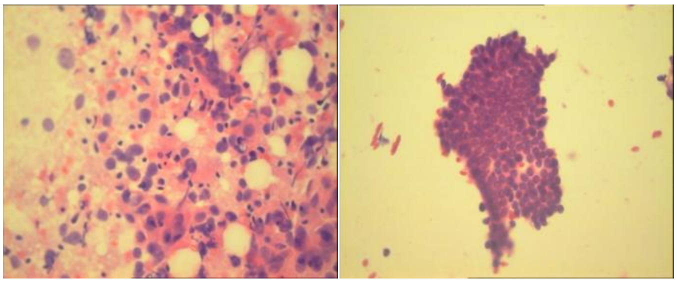


A B

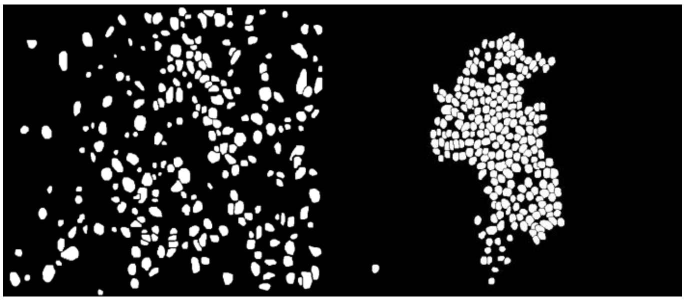
Figure 3: An example of segmented FNA images using Fuzzy C-mean Algorithm

3.3 Feature Extraction

The characteristics of benign cells are uniformity in appearance, whereas characteristics of malignant cells are irregularity in morphology (shape, size, and distribution). The extracted features that are used in this research can be categorized into three groups [4] (Binary features, Texture features, Color features). Figure 4 shows the detection of nuclei, where in this stage, features can be extracted to be ready in classification phase.



B A



D C

Figure 4: Original and Segmented FNA images

(A) Benign Case (B) Malignant Case
(C) and (D) are Segmented Images of Cases (A) and (B)

Breast cancer can be detected using three categories of features [4]. The first category is nuclei's size-related features. Malignancy cases can be recognized when there are large variations of cells sizes, whereas benign cases are identified when the cells with small uniform area. These characteristics can be measured by some features such as nucleus area, perimeter, and others. The second category is texture-based features. Some features of this category are co-occurrence matrix of gray-level values (GLCM) [25], mean and variance of pixel values in RGB channels [3], and run-length matrix of gray-level values (GLRLM) [26, 27]. The last category is nuclei's' distribution in the image -based features.

The total numbers of used features are 58, where mean and standard deviation are used for most extracted features and considered as two separate features, below is a detail description of all extracted features.

A- Binary Features

It is calculated from the binary image that produced from original color image. It contains set of nuclei that extracted from the image. The description of these features can be listed in the Table 1.

Table 1: Description of Binary Extracted Features from FNA images

Feature Name	Description
Area	The actual number of pixels of the nucleus
Perimeter	The sum of distances between each adjoining pair of pixels around the border of the nucleus
Eccentricity	The ratio of the distance between the foci of the ellipse and its major axis length
Major axis length	the length of the major axis of the ellipse that has the same normalized second central moments as the region
Minor axis length	the length of the minor axis of the ellipse that has the same normalized second central moments as the region
Distance from the centroid	the Euclidean distance between the geometric center of the nucleus and mean of geometric centers of all the nuclei in the image
Average area	It is calculated as the average number of nuclei pixel
Dispersion	It is define as a variation of cluster areas
Convexity	It is calculated as the ratio of nucleus area and its convex hull which is the area of the minimal convex polygon that contains the nucleus
Number of groups	calculate the number of groups in the image that weren't removed during the segmentation process

B-Textural feature It is used to obtain the texture information from the image, where, nucleus' texture is extracted. This information can be obtained by several features such as: Gray-Level Co-occurrence Matrix (GLCM) [17], which computes the relation of pairs among pixels and their colors and Gray-Level Run-Length Matrix (GLRLM) [27]. Description of these feature are illustrated in Table 2.

Table 2: Description of Texture Extracted Features from FNA images

Feature Name	Description
Gray-Level Co-Occurrence Matrix (GLCM)	
Contrast	The intensity contrast between a pixel and its neighbor over the whole image
Correlation	The correlation of a pixel to its neighbor over the whole image
Energy	Also known as **uniformity** - the sum of squared elements in the GLCM
Homogeneity	The closeness of the distribution of elements in the GLCM to the GLCM diagonal
Gray-Level Run-Length Matrix (GLRLM)	
SRE	Short run emphasis
LRE	Long run emphasis
GLN	Gray-level non-uniformity
RLN	Run length non-uniformity
RP	Run percentage
LGRE	Low gray-level run emphasis
HGRE	High gray-level run emphasis
SRLGE	Short run low gray-level emphasis
SRHGE	Short run high gray-level emphasis
LRLGE	Long run low gray-level emphasis
LRHGE	Long run high gray-level emphasis

C. Color Features

Color images contain three channels, each one of these channel is considered as a separate intensity image. The features are: (Red channel, Green channel, Blue channel, Gray Level of image) [3].

3.4 Feature Selection Methods (Dolphin Echolocation Algorithm DEA)

In this work, some modern feature selection methods are nominated to choose some good candidates features among all features. These FS methods are listed in Table 3. Meta-heuristic algorithms are also has used for several optimization problems such as feature selection problem. Genetic Algorithm (GA) is one of these algorithms that are successfully applied in FS [32].

Table 3: Description of nominated FS methods

Feature Selection Method	Description
Relief-F	It is **filter and supervised** approach, it computes the quality of the features according to how well their values differentiate data samples that are near to each other
Fisher	It is filter and supervised approach, it computes a score for a feature as the ratio of interclass separation and intra-class variance, where features are evaluated independently
Inf-FS	It is filter and unsupervised approach, it is graph-based method, each feature is a node in the graph, weights are given by mixture of correlation and standard deviation between feature distributions.
LaplacianScore	It is filter and unsupervised approach, the importance of a feature is evaluated by its power of locality preserving. In order to model the local geometric structure, this method constructs a nearest neighbor graph. LS algorithm seeks those features that respect this graph structure.

Dolphin Echolocation Algorithm (DEA) is the algorithm that is proposed in this research for feature selection. This algorithm is selected because it explores the whole search space in efficient way to find optimal solution. Dolphins at start search the whole search space to find the victim, when a dolphin reaches the victim, it will restricts its search, and will increases its clicks gradually in order to focus on the location. Dolphin algorithm has two steps: i) in the 1st step, the algorithm discovers all search space to perform a global search. This process will explore some random locations in the search space, and ii) in the 2nd step, it will focus on investigation the better results that produced from the first step. From these steps, its behavior can be concluded that dolphin algorithm inherit its characteristics from meta-heuristic algorithms with some improvements.

Flowchart of this algorithm is depicted in Figure 5, full details of DEA can be found in the original paper in reference [30].

3-5 Classification Methods:

Three different classification methods are utilized to test the features that are produced from FS process. The elected classification algorithms are as K-nearest neighbor (KNN), Support vector machine (SVM), and Back-Propagation Neural Network (BP-NN) [4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16]. These different classifiers are used to check how the method can influence the classification accuracy.

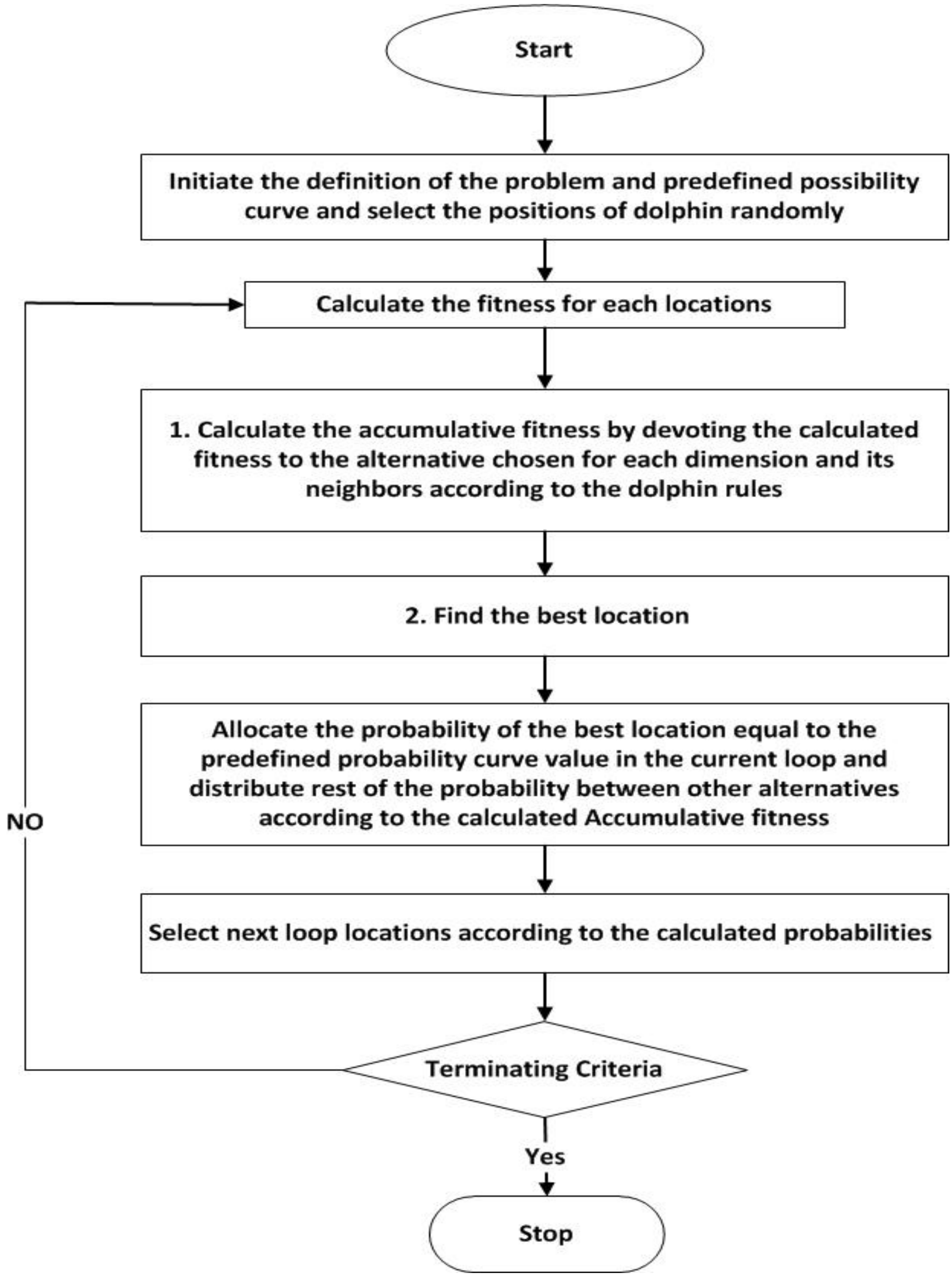


Figure 5: Flowchart of Dolphin Echolocation Algorithm

4- Experimental Results:

4.1 Dataset

For testing the existing and proposed algorithms, testing dataset is required. The most common dataset of FNA images is Wisconsin Database of Breast Cancer (WDBC), which can be obtained from repository of machine learning database University of California [28]. *WDBC contains 569 images* of two classes (benign and malignant).

4.2 Evaluation Metrics

In this research, four known metrics in images classification are used. These metrics are *Accuracy, Sensitivity, Specificity, and Precision*. The justifications of using these metrics are illustrated in [29], whereas the explanation of these metrics is listed below.

1. **Precision:** it is the possibility of recognizing the malignant cases correctly from all retrieved cases. It can be computed as in Eq. (1).

$$Precision = \frac{TP}{(TP + FP)} * 100 \quad \dots\dots\dots\dots\dots (1)$$

2. **Sensitivity**: it is the possibility of recognizing malignant (positive) cases correctly from all positive cases. It also called True positive rate (or Recall). It can be computed as in Eq. (2).

$$Sensitivity = \frac{TP}{(TP + FN)} * 100 \quad \dots\dots\dots\dots\dots (2)$$

3. **Specificity:** it is the possibility of recognizing benign cases correctly.It can be computed as in Eq. (3).

$$Specifity = \frac{TN}{(TN+FP)} * 100 \quad \dots\dots\dots\dots\dots (3)$$

4. **Accuracy:** It is the possibility of recognizing the malignant and benign cases together correctly. It can be computed as in Eq. (4).

$$Accuracy = \frac{TP + TN}{(TN + TN + FP + FN)} * 100 \quad \dots\dots\dots\dots\dots (4)$$

Where TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) are well known values of confusion matrix that resulted from classification process.

4.3 Experiments

For classification, SVM, BP-NN, and KNN classifiers are used. There were 569 images of benign and malignant cases. From each image, there are 58 features are extracted. Feature selection is utilized for dimension reduction using one of the following methods, (*Relief-F, Fisher, LaplacianScore, Inf-FS, Genetic algorithm (GA), the suggested Dolphin Echolocation*

Algorithm (DEA)). In addition to dimension reduction, the classification performance also will be improved due to it will depending on the most effective features only. The tables below will show the results of the four evaluation metrics. Each table will compare between traditional and meta-heuristic feature selection methods.

Table 4: Classification Accuracy for the three classifiers by using different feature selection methods

Feature Selection Method	Accuracy		
	SVM	BP-NN	KNN
Without FS	0.554	0.442	0.510
Relief-F	0.534	0.497	0.521
Fisher	0.543	0.538	0.534
LaplacianScore	0.600	0.541	0.522
Inf-FS	0.570	0.582	0.558
GA	0.673	**0.598**	0.630
DEA	**0.784**	0.571	**0.732**

In the results of Table 4, meta-heuristic algorithms (GA and DEA) are outperformed other traditional feature selection methods in terms of classification Accuracy.

Table 5: Classification Sensitivity for the three classifiers by using different feature selection methods

Feature Selection Method	*Sensitivity*		
	SVM	BP-NN	KNN
Without FS	0.554	0.492	0.530
Relief-F	0.558	0.522	0.521
Fisher	0.590	0.520	0.535
LaplacianScore	0.570	0.510	0.554
Inf-FS	0.622	0.602	0.599
GA	0.630	0.600	0.621
DEA	**0.653**	**0.603**	**0.642**

Table 6: Classification Specificity for the three classifiers by using different feature selection methods

Feature	*Specificity*

Selection Method	SVM	BP-NN	KNN
Without FS	0.754	0.642	0.610
Relief-F	0.770	0.663	0.612
Fisher	0.764	0.650	0.622
LaplacianScore	0.761	0.669	**0.690**
Inf-FS	0.785	0.730	0.643
GA	0.791	**0.733**	0.645
DEA	**0.793**	0.726	0.650

Table 7: Classification Precision for the three classifiers by using different feature selection methods

Feature Selection Method	**Precision**		
	SVM	BP-NN	KNN
Without FS	0.784	0.666	0.650
Relief-F	0.781	0.654	0.653
Fisher	0.785	0.665	0.685
LaplacianScore	0.787	0.667	0.688
Inf-FS	0.776	0.695	0.697
GA	0.789	**0.750**	0.711
DEA	**0.811**	0.726	**0.721**

From above results, *Tables 4,5,6 and 7*, DEA surpasses GA and other FS algorithms. This is because, the bio-inspired algorithm such as DEA and GA are outperformed the other traditional FS algorithms due its characteristics of reducing search space of problem. These bio-inspired algorithms reduce the features approximately to the half, where only the effective features will be selected. This, in turn, will increase the accuracy of classification where the useless features will be omitted. Among all used classifiers and after feature reduction, SVM classifier outperforms other classifiers.

5- Conclusion

The aim of the work is to test DEA algorithm in feature selection problem. In the experiments, 569 FNA images are used and fuzzy C-mean clustering algorithm is utilized for nuclei segmentation. Three categories of features (binary, texture, and color features) are used in feature extraction process that is produced 58 features. Afterward, feature selection is applied for reduce number of features (approximately to the half, 30 features) as well as to select most effective features in classification process. In this process, five FS methods are used for comparison with the proposed DEA algorithm (Relief-F, Fisher, LaplacianScore, Inf-FS, and Genetic algorithm (GA)). The results illustrate that meta-heuristic algorithms, GA and DEA, outperform the other traditional FS methods. In Classification process, three different classifiers (SVM, BP-NN, and KNN) are applied to test the selected features that resulted from all types of FS methods. The experiments show that SVM classifier gives the best results.

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