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Hybrid Genetic Algorithm with Tabu Search with Back-Propagation Algorithm for Fish Classification: Determining the Appropriate Feature Set

Mutasem K. Alsmadi

Department of MIS, College of Applied Studies and Community Service,

Imam Abdulrahman Bin Faisal University, P.O. Box 1982, Dammam, Saudi Arabia.

Abstract

Uncontrolled environmental settings, pose variation, and inadequate training data are among the reasons why wild Fish Classification (FC) and detection are still problematic. The present study proposes a hybrid Tabu search with the Genetic Algorithm with a Back-propagation algorithm (GTB Classifier) for FC by extracting the suitable feature set based on a combination between extracted texture, shape, and color signature features. The fish images were classified into Garden, Predatory, Food, and Poison fish families. The proposed classifier was tested in this study utilizing 24 fish families, each containing diverse species. For the back-propagation algorithm, the achieved classification rate was 82.1%, while that of the proposed GTB Classifier was 87%.

Keywords: Shortest Path; Color Signature; Graph; Color Histogram Quantization; Texture; Shape Measurements; Features extraction; Tabu Search; Meta-heuristic Algorithm and Back Propagation Algorithm.

1. INTRODUCTION

Humans have been carelessly and frequently intervening with the natural functioning of the environment, and for several living creatures, such careless interventions have harmed their existence. The dispersal and profusion of the natural life, in general, have equally been profoundly altered by such interventions, as can be observed among fish. The global fish fauna has faced a significant amount of loss which has been primarily caused by water pollution and destructive practices of fishing. The biodiversity of local fish has been dramatically affected by the exploitation of resources including mining and forestry. Dam construction for hydroelectric power production has also been known to affect the biodiversity of fish. The expansive alternations in aquatic life can lead to reproductive segregation between certain species [1, 2].

The availability of machine learning methods and multimedia could considerably accelerate the discovery of new species [3]. The specimens' diagnostic features can be automatically recognized through the selection made between two options at each step, following the absence or presence of a given feature, the number of scales, or the ratios between the ratios of body measurements. In fulfilling the requirements of species identification, more efficient methods have been currently sought by taxonomists. These include the construction of digital image processing and techniques of pattern recognition. It should be noted that the use of pattern recognition techniques has been observed in the identification of plants, insects, spiders, plankton, and other domains as well [4-20].

Classification of fish images still has problems [9, 11, 21-35], so any fish classification method that is proposed should address different issues such as; feature variability, arbitrary fish size, segmentation failures and environmental changes. Accordingly, the present study will attempt to classify fish images into Garden, Predatory, Food and Poison fish families .

The present paper comprises five sections altogether. Following the introduction section, Section 2, reviews the literature of FC, while Section 3, explains the methodology utilized in this study. The obtained results of the Classifiers and other comparable methods are illustrated in section 4. This paper is concluded in the last section namely Section 5.

2. LITERATURE REVIEW

A prototype for FC was presented in Alsmadi et al. [36]. It comprises a combination of the size and shape features extracted using measurements of geometry and distance as shown in figure 1. In their work, the authors employed twenty different fish classes whereby each class comprises different fish species. The neural network (NN) connected with the BP algorithm on the employed fish images dataset was applied in the process and the total achieved accuracy was 86%. The test carried out on the proposed method proved its effectiveness in classifying the fish image given into its respective category.

hybrid metaheuristic was used in Badawi and Alsmadi [32] for general FC purposes. The classification task was carried out based on significant features extracted from shape and texture measurements. In other work, a hybrid metaheuristic was used in Alsmadi et al [35] for generic FC purposes. The classification task was carried out based on significant features extracted from texture and shape features extracted. The classification accuracy results were 82.25% and 90% for the backpropagation algorithm and the MA-B algorithm respectively.

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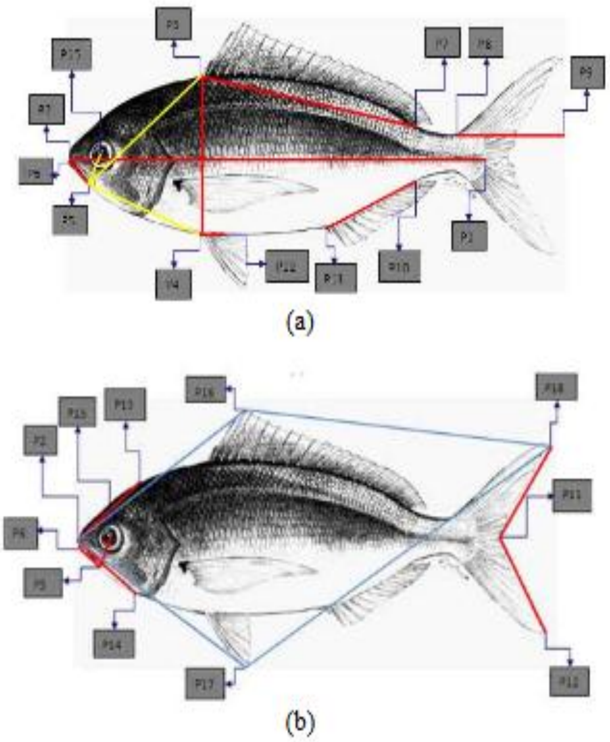


Figure 1: Distance and geometrical measurements [36].

The robust features selection method for FC was presented in Hnin and Lynn [7]. In their study, the authors applied Machine Learning techniques in addition to a combination-based features selection method. The proposed technique enabled the achievement of a subset with fewer features and accurate classification was achieved as well. The obtained results from the utilized methods were compared with the obtained results from the available correlation-based method of feature selection, the authors concluded that the combination-based feature selection method was able to define the dimensionality course. This, in turn, leads to better prediction performance, fewer requirements of measurement and storage, in addition to decreasing the training and prediction times.

The performance of FIRS has been demonstrated in Pornpanomchai et al. [15]. An FIR encompasses a computer-operated fish image recognition system that is based on shape and texture. An experiment was carried out involving 900 images from 30 species of fish. The 900 fish images were classified into two datasets as follows: training dataset (600 images), and testing dataset (300 images). The proposed system was assessed and compared in terms of recognition accuracy with the use of two recognition techniques namely ANN and FDM, and the results were as follows: the proposed system was able to classify all of the 30 species and achieved 81,67% and 99.00% classification accuracy using EDM and ANN techniques. Figure 2 illustrates the proposed fish image recognition structure system.

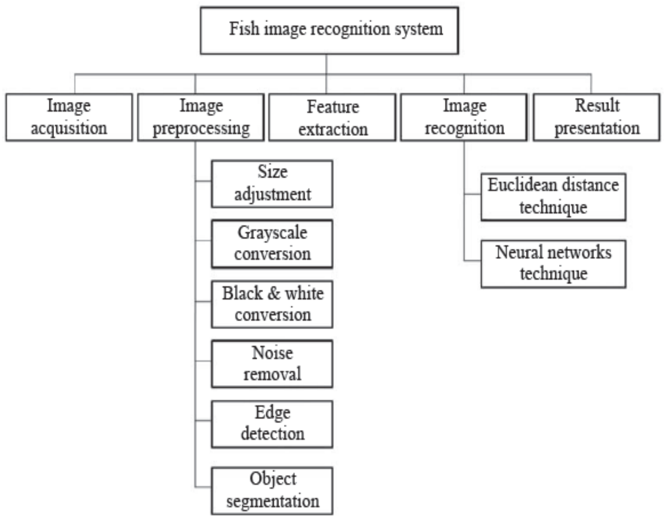


Figure 2: Structure chart of the proposed fish image recognition system [15].

Alsmadi et al. [18] demonstrated combined methods based on the color texture features. For extracting color texture features the Gray-Level Co-Occurrence Matrix (GLCM) was employed and then the back-propagation algorithm was tested utilizing twenty different fish classes comprising a diverse quantity of fish species each. The authors employed the back-propagation algorithm, the overall classification accuracy result was 84%.

3. MATERIALS AND METHODS

This work aims to determine the largest set of features. Therefore; 54 different features were calculated for each fish species, based on the extracted information type they can be divided into three categories and the number extracted features for these categories are 15 texture features; 14 Color features and 25 Shape features. The calculation of these extracted features was achieved based on the fish object, the fish object was obtained using a cropping operation to subtract the fish object from the image background to be utilized for shape and texture features extraction and to obtain the ventral part of fish for color features extraction.

3.1 Data Set

In this study, 500 distinct fish images were divided into 350 images for the training phase and 150 images for the testing phase, the dataset was obtained from [37]. The dataset involves three different fish classes comprising a diverse quantity of fish species each as following:

1. Dangerous Fish: Carcharodon Carcharia, Hydrocynus Goliath, Atractosteus Spatula and Carcharhinus Leucas fish species.
2. Poison Fish: Porcupine, Red Snapper, Thorn and Trigger fish species.
3. Garden and Food Fish: Albulidae, Anomalopidae, Istiophoridae, Priacanthidae, Acestrorhynchidae, Triacanthidae, Stromateidae, Drepanidae, Acropomaatidae, Sillaginidae, Caesionidae, Leiognathidae, Scombridae, Siganidae, Platycephalidae and Megalopidae fish species.

3.2 Texture Features

One of the most common features for object classification is grayscale texture analysis. Which provides enough information to be used in solving many object classification tasks.

Graph theory for texture analysis proposed by [50] was used in this work. In this method, the image is represented as an undirected weighted graph, where each pixel of a given image is converted into vertices and discovers the shortest direction between some selected points in different scales and directions. The method converts an image to an undirected weighted graph that shows the relations between neighborhoods in an image. The image gray levels represent the weights. Then, the shortest paths between diverse square regions are determined; like a traveler investigating the shortest paths in a landscape.

The graph is represented as $G = (V,E)$ since each pixel $I(x,y)$, $y = 1{:}N$ and $x = 1{:}M$ is considered as a vertex v in V of G. Each vertex is represented as a pixel of an image. Then the edge e in E links two vertices (v_i, v_j) the Chebyshev distance between v_i and v_j does not exceed a predefined value. Then the specific calculation for mean different average gray-level intensities is used for finding similar patterns to predict classes.

The Dijkstra's algorithm [51] is used to find the shortest paths, to do this, the shortest paths are computed between four ending and starting points (vertices) as follow:

- The diagonal paths, between the diagonal points, are used of the texture (at degrees 45 and 135).
- The horizontal path, between the middle points, is used on the right and left sides (at degree 0).
- The vertical path between the middle points is used for the lower and upper sides (at degree 90).

This method provides an image texture signature by separating at different angles in the texture patterns from the pixels of the same gray levels. However, to have a good texture pattern with global Local features and to provide context information about pixel surroundings, the original texture is divided into non-overlapping boxes with size r, then the shortest paths are computed between the four stated points (at degrees 0, 45, 90 and 135).

Three feature vectors are obtained in this method, the first and second represents a texture pattern produced by the boxes of size r, then the average $(\mu_0, \mu_{45}, \mu_{90}, \mu_{135})$ and the standard deviation $(\delta_0, \delta_{45}, \delta_{90}, \delta_{135})$ of the four shortest paths are computed for each box. While the third feature vector is the concatenation of the two previous feature vectors, finally the three feature vectors as follow:

$$\alpha \rightarrow = [\mu_0, \mu_{45}, \mu_{90}, \mu_{135}]$$

$$\beta \rightarrow = [\delta_0, \delta_{45}, \delta_{90}, \delta_{135}]$$

$$\gamma \rightarrow = [\alpha \rightarrow, \beta \rightarrow]$$

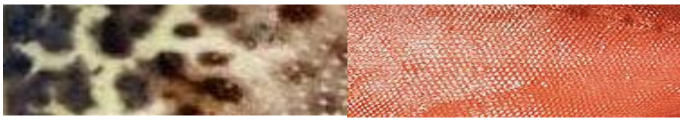
To analyze the texture image for each box size, the feature vectors are computed for $r = \{4, 5, 8, 10, 20\}$, having 15 features as follow:

$$F_{v1} = [\alpha \rightarrow_4, \alpha \rightarrow_5, \alpha \rightarrow_8, \alpha \rightarrow_{10}, \alpha \rightarrow_{20}]$$
$$F_{v2} = [\beta \rightarrow_4, \beta \rightarrow_5, \beta \rightarrow_8, \beta \rightarrow_{10}, \beta \rightarrow_{20}]$$
$$F_{v3} = [\gamma \rightarrow_4, \gamma \rightarrow_5, \gamma \rightarrow_8, \gamma \rightarrow_{10}, \gamma \rightarrow_{20}]$$

The aim here is to perform the shortest texture variation paths at different image scales.

3.3 Color Features

According to the previous research and fish biologists [38, 39], the ventral colorations of the fish object contain very imperative features to distinguish between diverse fish species. In this work, ventral colorations were used to distinguish between the fish species. For example, the non-poison fish species have fewer color variations compared to poison fish species which have more color variation, as shown in figure 3.



(a) (b)

Figure 3: Ventral part different fish species.

After subtracted the ventral part of the fish object using a cropping operator, the ventral part image will be used for the color features extraction. RGB color value will be used to compute the Hue, Saturation, and Value (HSV). For color extraction of the ventral fish object, each image pixel is identified in a histogram form by image color quantization in 72 bins (3 bins of component V, 3 bins of component S, and 8 bins of component H), which is effective for decreasing the computational complexity without decreasing the image quality [40]. The steps of color feature extraction using HSV are CHQ .

After the HSV matrix is obtained, the process of the CHQ is conducted to enhance the performance and decrease the computational cost from the calculations of an image pixel. CHQ is performed as in [41]. After that, the vector of color feature is converted from a three-dimensional (HSV vector) to one-dimensional to form a histogram as in [41].

3.4 Geometric Features

In this work, the feature point-based method was used to find a highly distinguishable 23 Feature Points (FPs) for shape features extraction. After that; these FPs were used to extract 25 geometric features using length and ratio measurements. Therefore; several FPs need to be determined manually on the fish shape. FPs are detected at points like; the start of the dorsal fin, the start of fish mouth, eye center, and the start of the caudal fin, etc. Figure 4 illustrates the locations of the FPs.

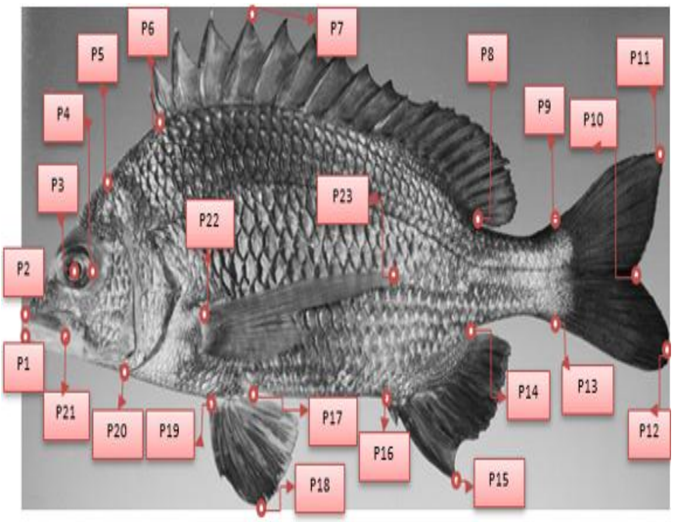


Figure 4: The locations of the FPs.

However; before discussing geometric features, 23 lengths between two FPs were determined such as L17= |P1-P7|, L13= |P1-P3|, L11,12=|P11-P12|, and L1,10=|P1-P10|, as shown in Figure 4. Therefore; 15 ratio features were calculated such as R1=L17/L13, and R2=L11,12/L13. Further, 10 angle features were calculated such as A1=LP15P11P7, A2=LP18P6P11, A3=LP19P1P7 and A4=LP12P9P11.

3.5 The Proposed Hybrid GTB Algorithm

In this work, A feedforward neural network consists of three layers [42-44], which are the input, hidden and output layers, the neurons number in the input layer equals to the input extracted features number, a hidden layer has 30 neurons and finally, the output layer has 24 neurons (which equals to fish families that will be classified). BP algorithm was used to distinguish the fish species based on the extracted features.

3.5.1 Metaheuristic Algorithm

A Metaheuristic algorithm (Genetic algorithm with Tabu search) was utilized to tune and enhance the BP algorithm weights, the Metaheuristic search techniques were used to handle the major limitations of BP such as a slow convergence rate [45, 46]. Basically, in the Tabu search algorithm, short-term memory is employed to use controlled randomization to make a move and a longer-term memory for search space diversifying using the moves frequency information [47]. By repeating the process of neighborhood generation and managing the long- and short-term memories the algorithm proceeds iteratively until meeting a termination condition.

Figure 5 illustrates the flowchart of the proposed metaheuristic search techniques with the BP algorithm. Tabu search local search was used to enhance the exploitation process of the GA. Table 1 displays the parameters setting of the proposed GTB Classifier.

Table 1: Parameter setting of the proposed Algorithm.

Parameters	Values
Short term memory	3
Generation	1100
Long term memory	50
Fitness Value	0.8
Tabu criteria	0.3
Crossover	08
Crossover Type	Single Point
Mutation Rate	0.02

The process of the proposed GTB Classifier is illustrated as follows:

1. Initialization: a binary number was used to denote every solution in the search space. Where a real value (fraction number) is used to represent the chromosome in the weight matrix.

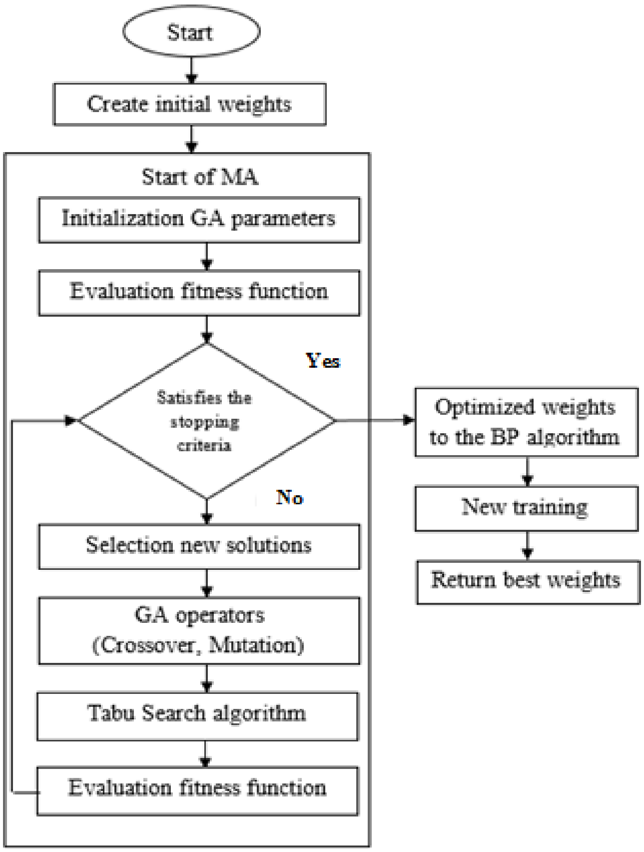


Figure 5: The diagram proposed the GTB algorithm.

2. Selection: To generate new solutions that have higher fitness values, the chromosomes with the highest fitness value are selected for reproduction in the population space. A roulette wheel selection is employed in this research as a mechanism for selection.
3. Crossover: Crossover combines two parents' chromosome information and creates a new children's chromosome which contains parts of genetic material from each parent.
4. Mutation: Mutation works by taking one parent chromosome and randomly creates a child chromosome by exchanging some of the bits in the parent chromosome.

5. Fitness Function: it evaluates the quality of the candidate solutions based on the domain of the problem. This research employed the Variance Account Function (VAF) which can be calculated as the following [26]:

$$V = 1 - \frac{variance(y - y\_test)}{variance(y)}$$

The real output is represented as *y*, *y_test* is the model estimated output, and to result in the output *V*, *VAF* is computed for both signals which are used for model correctness evaluation, by comparing the expected model output with the real output.

Tabu Search algorithm will commence exploitation of solutions spaces once the selection mechanism and the genetic operators (e.g., crossover and mutation) of the GA are accomplished. The GA generates a new population of solutions from older populations that goes through crossover and mutation processes and ends up with the selection mechanism of best solutions found so far. Hence, the GA provides the Tabu Search with several elite solutions in terms of quality and diversity that are candidates for further quality improvement to seek global optimum and escape a local optimum. Generally, Tabu Search algorithm acts as a local search routine and iteratively searches for better quality solutions by starting from a current solution (e.g., provided by the GA) and generates the next best solution in a given neighborhood around that current solution. However, sometimes this newly generated solution can be worse than the current solution in terms of quality. Nevertheless, in either case, this behavior of the Tabu search guarantees to avoid the convergence towards a local minimum. To implement this behavior in a controlled manner, the Tabu search mainly uses a short-term memory to save the performed moves in the neighbors around the current solution, this is termed as “tabu solutions”, recently visited solutions [47, 48]. On the other hand, tabu search incorporates explicit strategies to control the exploration of the search space in an efficient way, where this incorporation might lead to a relatively balanced exploration vs exploitation. These groups are categorized into two terms; intensification and diversification. To find the best solution, the intensification strategy provides an extensive search of neighborhood structures (or rather the path toward the best solution) around an elite solution (e.g., weights of the BP algorithm), while the diversification strategy provides large permutations (e.g., crossover and mutation) of a solution to converge towards other neighborhood structures around an elite solution. When the intensification strategy is stagnated, where the search converges towards poor quality solutions, or when the extensive search is unable to generate elite solutions anymore, then the diversification strategy comes to an action to break the stagnation and commence a new generation of elite solutions. Both strategies are applied alternatively depending on the problem specification.

Once a significant improvement in the weights of the BP algorithm in terms of the fewest selected features possible, the tabu search passes those optimized weights to the genetic algorithm's evaluation function.

4. RESULTS AND DISCUSSION

Table 2 shows the number of features extracted using the proposed features extraction methods, where 14 color features using HSV color space, 15 texture features using GLCM, and 25 shape features using distance and angle measurements .

In this work, 25 features were extracted using shape measurements; these features are extracted using shape measurements and were minimized into 15 features based on selecting only one feature among the values of the converged features to determine the robust features among the features extracted that will help to get high classification accuracy. Features minimization has been done using the visualization tools which are provided in the Weka classification software.

Table 2: Features extracted number.

Methods	Features Extracted Number	Features Extracted Number after Selection
Texture features	15	15
Color signature features	14	14
Shape features	25	15

In the proposed classifier, the process of the parameters learning using MA and BP algorithm consists of two steps, firstly; the initially obtained weights by NN are optimized and enhanced by the proposed MA, where the proposed MA is used to enhance and improve the obtained weights (solution quality) by enhancing and increasing the fitness cost number. Secondly; the BP algorithm is used to train the weights that were optimized by the MA. Table 3 shows the overall classification accuracy results for the back-propagation algorithm and the proposed hybrid GTB algorithm.

Table 3: Overall classification accuracy results using the proposed classifiers.

Classifier	Classification accuracy
BP algorithm	82.1%
Proposed GTB classifier	87%

As shown in table 4, the proposed GTB classifier performs better compared to other traditional methods such as [32, 49] in terms of speed and classification accuracy. Many researchers mentioned that the global variations in appearance and expression of fish have less influence when using texture and color signature features. Accordingly, the best accuracy results for BP and GTB Classifiers were at 85% and 91%, while the less accurate were at 79% and 83% respectively (see figures 6 and 7). Likewise, the developed hybrid GTB classifier outperforms the traditional BP algorithm based on the features extracted. The classification accuracy of the BP classifier was significantly improved by the hybridization with Tabu search with GA through optimizing the weights of the BP classifier.

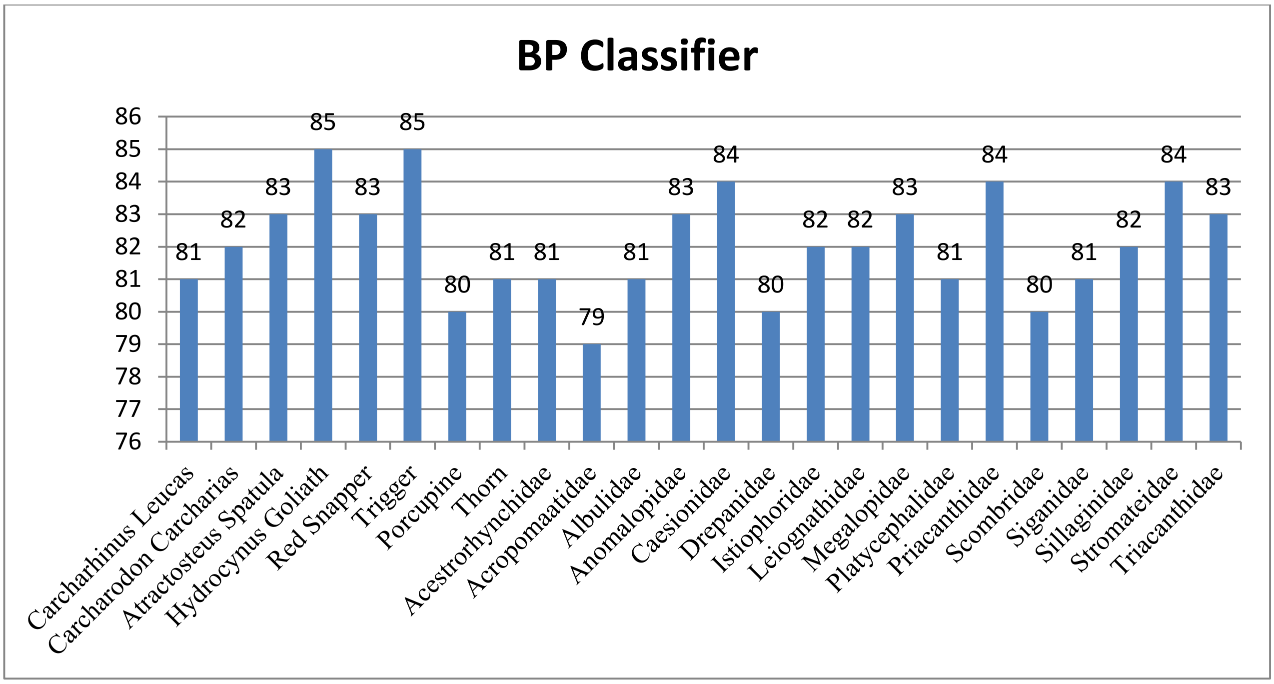


Figure 6: Recognition accuracy results using BP classifier.

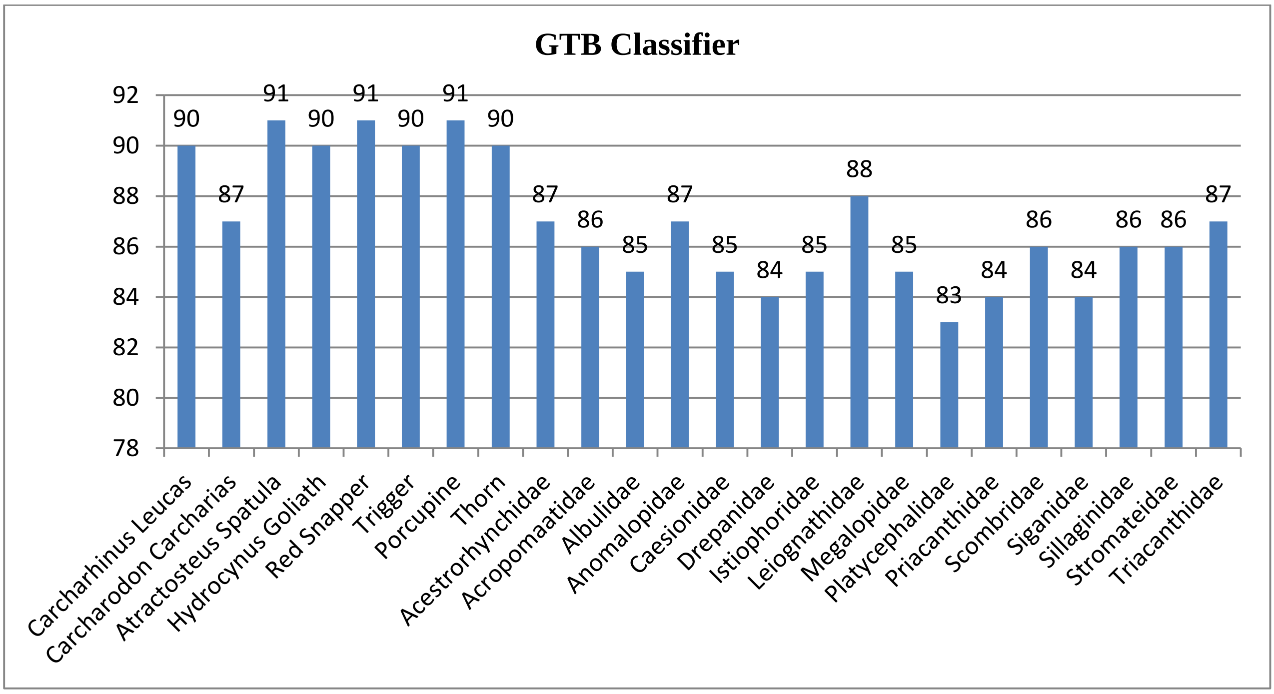


Figure 7: Recognition accuracy results using GTB Classifier.

Compared with other previous methods [32, 49] the used features extraction methods and classifiers in this work show higher performance in terms of classification accuracy results with a percentage of 82.1% and 87%, while GAGD-BPC [49] and GAILS-BPC [32] outperformed the proposed BP classifier in terms of classification accuracy results with a percentage of 83.2% and 85% as shown in table 4. As mentioned before, many researchers stated that the global variations in appearance and expression of fish have less influence when using texture and color signature features. Moreover, the GTB Classifier outperformed the BP classifier in terms of classification accuracy.

Moreover; the GTB classifier was compared with implemented Support Vector Machine (SVM) using the same fish dataset based on the extracted features to validate the obtained results more effectively. As shown in Table 7, the obtained results show that the proposed hybrid BP and GTB classifiers significantly outperformed the RBF network.

Table 4: A Comparison between the obtained accuracy results of the proposed Classifiers and other methods.

Classifiers	Classification Accuracy
BPC [32]	82%
GAILS-BPC [32]	85%
BPC [49]	81%
GAGD-BPC [49]	83.2%
BP classifier	82.1%
Proposed GTB Classifier	87%
SVM classifier	81.7%

5. CONCLUSION

This work presented a fish image recognition based on the extraction of texture, color signature and shape features. The combination of color features that were extracted using HSV color space, texture features were extracted using graph theory and shape features were extracted using length and ratio measurements to extract robust features for FC. In this work, the parameters learning the process of the MA and BP algorithm consists of two steps, firstly; the initially obtained weights by NN were optimized and enhanced by the proposed MA, Secondly; the BP algorithm is used to train the weights that were optimized by the MA. The BP and the hybrid GTB classifiers show superior performance over the recent methods with a classification accuracy of 82.1% and 87% respectively and successfully classified the fish images into predatory, poison, garden, and food fish families.

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