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Fish classification using extraction of appropriate feature set

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ABSTRACT

The field of wild fish classification faces many challenges such as the amount of training data, pose variation and uncontrolled environmental settings. This research work introduces a hybrid genetic algorithm (GA) that integrates the simulated annealing (SA) algorithm with a back-propagation algorithm (GSB classifier) to make the classification process. The algorithm is based on determining the suitable set of extracted features using color signature and color texture features as well as shape features. Four main classes of fish images have been classified, namely, food, garden, poison, and predatory. The proposed GSB classifier has been tested using 24 fish families with different species in each. Compared to the back-propagation (BP) algorithm, the proposed classifier has achieved a rate of 87.7% while the elder rate is 82.9%.

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1. INTRODUCTION

Currently, nature is suffering from the misuse of humans. As a result of uncontrolled human behaviors, many aspects of normal life are beginning to die off. One of the most threatened normal life aspects is the fish environment. In recent years, the waterfront has many challenges and losses due to many factors, the most important of which are water pollution and overfishing. Moreover, building dams to generate electric energy has a negative impact on fish resources. These and other factors may lead to dramatic changes in the aquatic environment, including the extinction of some fish species [1], [2].

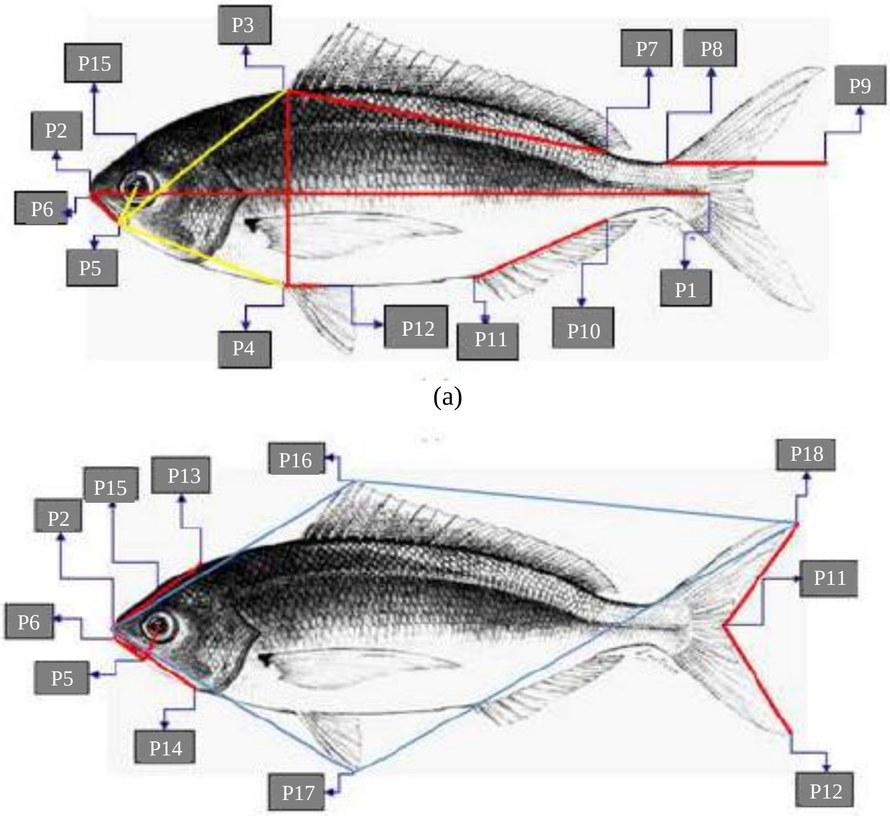
The availability of machine learning techniques and the use of technology may strongly help in classifying fish of various types and identifying new strains of them that are vulnerable to extinction [3]. The characteristics of the different fish species can be determined by comparing them and determining the availability or absence of specific features. These criteria can be determined by specifying a specific range of ratios for different body measurements. Classification professionals are currently seeking to use more effective methods in the classification process, including the use of pattern recognition techniques and digital image processing. Pattern recognition technology is currently used in many fields to classify many types, such as insects, spiders, plants, parasites and other fields [4]–[18].

There are many problems in the process of fish images classification [3], [11], [13], [19]-[32]. Therefore, any electronic fish classification method should take into consideration a set of problems, which are the wrong division, different fish sizes, orientation, different features in the same type, environmental variables, poor quality images, conditions in which imaging and physical shaping. This study will classify fish into predatory, poisonous, garden and edible species.

The particular paper is structured as; the literature review is presented in Section 2. Utilized material and method are introduced in Section 3. In addition, the proposed hybrid genetic algorithm that integrates the simulated annealing (SA) algorithm with a back-propagation algorithm (GSB classifier) is also presented in Section 3. Section 4 presents the achieved results based on the proposed classifiers and other comparable classification methods. Finally, a conclusion is introduced in Section 5.

2. LITERATURE REVIEW

Alsmadi [33] have introduced a prototype for fish classification which consists of a feature set obtained from size and shape measurements. Geometry and distance measurements have been applied as well in their work as shown in Figure 1. 20 fish families have been used by the authors each of which contains different fish spices. The accuracy of their results was 86% based on applying the algorithm of neural network on the dataset with the back-recognition. Tests on the proposed method show that the method can effectively classify fish into its category. The image of fish is also classified as poisonous or non-toxic and then given to their family.



(a)

(b)

Figure 1. Determined anchor points for extracting the shape features using (a) distance measurements, and (b) angle measurements [33]

Badawi and Alsmadi [30] use hybrid meta-heuristic algorithm (genetic algorithm with iterated local research) and BP algorithm (GAILS-BPC) for general fish classification. The classification function is based on important features derived from texture and shape measurements. Then again, Alsmadi [34] proposed a hybrid Tabu search with the genetic algorithm (GA) with a back-propagation algorithm (GTB classifier) for fish classification by extracting the robust feature set relying on a combination between extracted shape, color signature, and texture features. The dataset utilized in this examination included 24 fish families from four unique classes to be specific: garden, predatory, food, and poison fish families. The outcomes got by the investigation demonstrate a rating of 82.1% for the back-engendering calculation and 87% for the proposed GTB calculation.

Another study from Alsmadi *et al.* [32] was established in which a system was designed to classify fish organisms based on texture, statistical measurements, and anchor points. A general classification of fish that is implemented through the application of the meta-heuristic algorithm (genetic algorithm with SA) with BP algorithm (MA-B classifier). In this research work, fish were classified into two main families, namely the dangerous fish family and the non-dangerous fish family. Dangerous fish were divided into two categories: predatory or poisonous fish, while non-predatory fish were classified into garden fish and edible fish. To test the proposed system, 24 fish groups were used, each containing different types of fish according to the previous classification. In the system experimental tests, 400 images were utilized, including a set of 150 images for the testing phase and 250 images for training phase. The accuracy rate achieved using the proposed system is 90% compared to the back-propagation algorithm, which achieved an accuracy rate of 82.25%.

The methodology that was used in Chuang *et al.* [35] is based on choosing parts of the fish body that satisfy certain fitness and relaxation standards. This is performed to ensure the object matching process. The non-rigid part of the model is then learned using the fitness, separation, and discrimination criteria. A bilayer hierarchy is created by the uncontrolled aggregation approach. Coarse marks are assigned by partial classification. This is used to exploit information from obscure images. The non-controlled, non-solid learning algorithm proposed is shown in Figure 2. The accuracy of this approach is 93.8% for public and private underwater fish images.

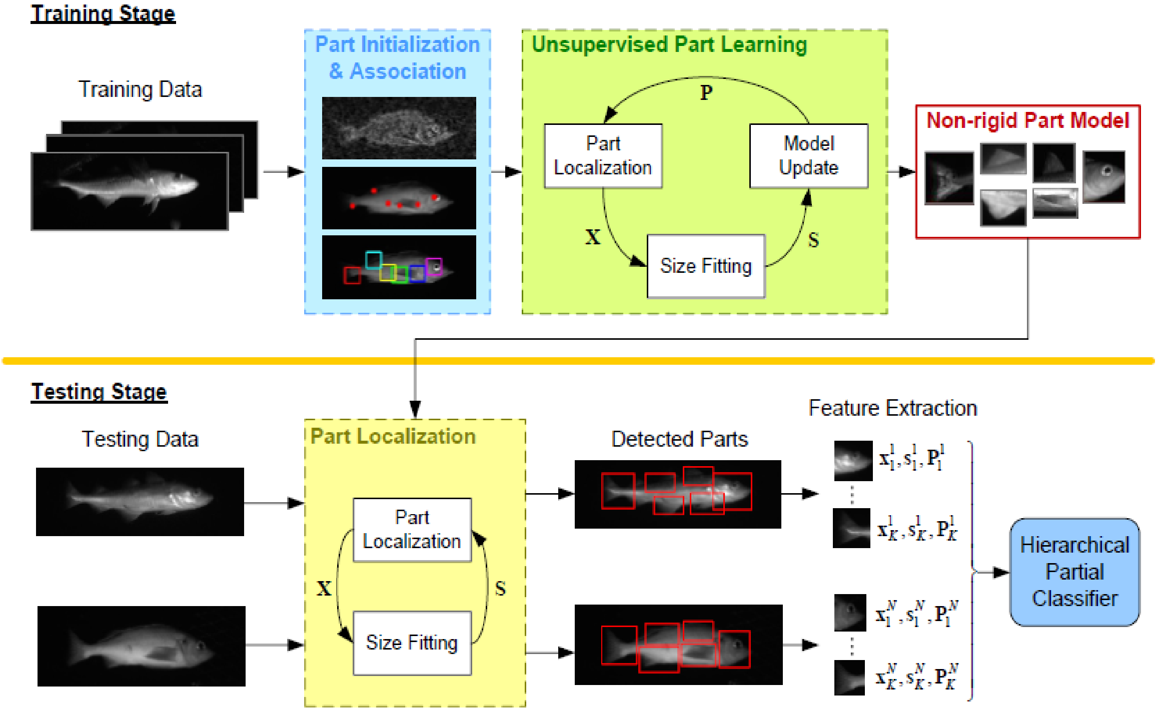


Figure 2. Proposed unsupervised non-rigid part learning algorithm [35]

Iscimen *et al.* [36] have introduced a database comprising fish species and their classification. The study concentrated on fish photos in Turkey seas to build the database. Biometric points on the fish have been used to extract the set of features used in the identification process. The biometric measurement has been collected using three different techniques namely, quadratic network technique, Euclidean network technique, and triangulation technique. Figure 3 describes the fish biometric landmarks. Naive Bayesian classifier was used to generate the classification system for 7 families an accuracy rate of 93.10% has been achieved while for the other 15 families the accuracy rate was only 75.71%.

Alsmadi *et al.* [24] introduced combined methods depending on the color texture measurements extracted features. Gray-level co-occurrence matrix (GLCM) approach is utilized for extracting color texture features. The BP algorithm was applied upon 20 distinctive fish families all of which includes a diverse fish species quantity. The BP algorithm has been utilized with an overall classification accuracy result of 84%.

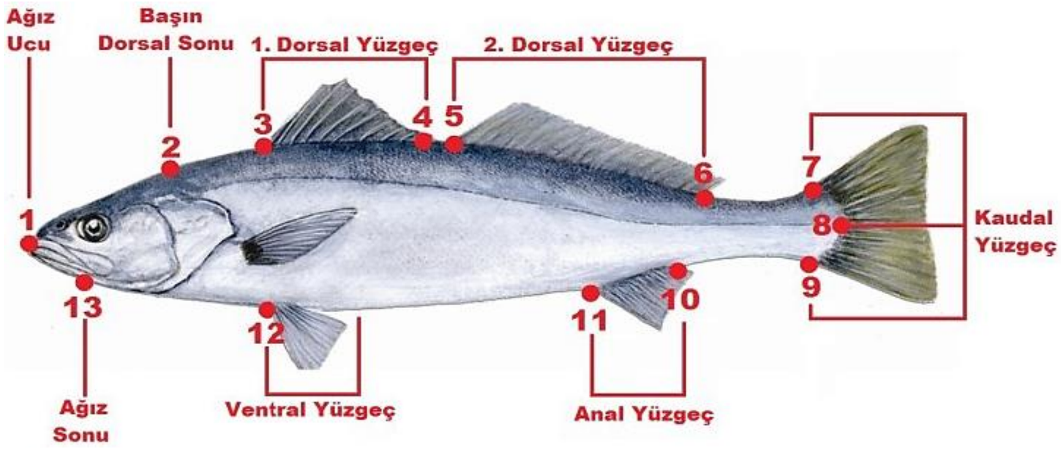


Figure 3. Representation of biometric landmarks in fish [36]

3. MATERIAL AND METHOD

In this section, materials and used methods are introduced. Section 3.1 introduces the used data set. In Section 3.2, color features extraction method is presented. Color texture features extraction mechanism is shown in Section 3.3. Section 3.4 overviews the mechanism of calculating shape features using anchor points.

3.1. Data set

The images used in this investigation are gotten from the LifeCLEF 2015 fish task (https://www.imageclef.org/lifeclef/2015/fish) and fish-base (https://www.fishbase.se/home.htm). Where 500 distinctive fish images have been decided to make the investigations of this examination. 350 of these images have been applied for the neural learning stage and 150 images for the testing stage.

3.2. Color features extraction

The shade of the fish object ventral has vital highlights as the scientists and past investigates announced [23], [24], [26], [27], [32], [33]. Such highlights could be adequately used to recognize distinctive fish families/species. In this work, the ventral hues will be utilized to discover the contrasts among poison and non-noxious fish families. Be that as it may, non-toxic fish families as shown in Figure 4(a) have fewer shading varieties whenever contrasted with toxic families as shown in Figure 4(b).

(a) (b)

Figure 4. Ventral part for fish families: (a) non-poison, and (b) poison

The ventral part of the image will be used to extract color features. The cutting operator can be used to perform the process of cutting the ventral part of the fish object. In this proposed work, some color features will be extracted from each image and then compared based on these features. Based on the probability theory, the image color composition will be viewed as a color distribution. Histogram could be used to view the discrete probability distribution. Color histograms are effective to infer the properties of an image. It helps to determine the possibility of accurate colors in the image. According to probability theory, the probability distribution can be distinguished by statistical moments. Therefore, the use of statistical moments may help to determine the probability distribution of colors in images. In this research work, the extracted features will be the moments of the color distribution [37]. These moments will be the classification features. It has been proven that first-order (mean), second-order (standard deviation) and third-order

(skewness) are effective and efficient in representing image color distribution. If the value of the i^{th} color channel at the j^{th} image pixel is Pij then the color moments are calculated as follows:
1st order moment (mean)

$$E_i = \frac{1}{N}\sum_{j=1}^{N} P_{ij} \tag{1}$$

2nd order moment (standard deviation)

$$\delta_i = \sqrt{\left(\frac{1}{N}\ \sum_{j=1}^{N}\left(P_{ij} - E_i\right)^2\right)} \tag{2}$$

3rd order moment (skewness)

$$S_i = \sqrt[3]{\left(\frac{1}{N}\ \sum_{j=1}^{N}\left(P_{ij} - E_i\right)^3\right)} \tag{3}$$

Representation features based on color moments are highly compact if compared with other color features [37]. The color content of each image channel in color moments is presented by 9 numerical values (each layer has 3 values). The images used in the proposed system will be represented in the red, green, blue (RGB) color space. In spite of the informality and device dependency of such space, it is still trusted for representing color images. The use of RGB color space should not be problematic since there will be a preprocessing step before its usage.

The preprocessing step will be performed using the ranklet transform. It is a good choice since it has the advantage of generating three images in different orientations (diagonal, horizontal, and vertical) on each image layer (red, green, and blue) [37]. The ranklet transform produces three images for the red layer, three images for blue layer, and three images for green layer (a total of 9 images). Figure 5 illustrations the preprocessing step.

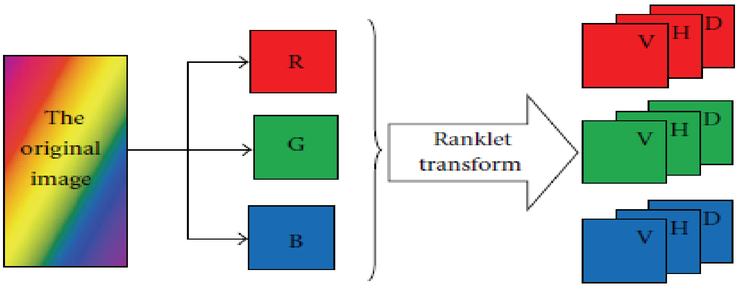


Figure 5. The preprocessing step using the ranklet transform [37]

The next step after the preprocessing step is to extract the image color features. Since there are 9 generated images in all layers, calculations take place to obtain the three-color moments for each image using (1) for the mean, (2) for the standard deviation, and (3) for the skewness. For each image in the database, an image features vector is calculated. The vector is calculated using the different moments mean, standard deviation, and skewness. Then the 3 values are concatenated to form the image features vector with 27 values that represent the image. The vector is used to be compared with other vectors to find the similarities.

3.3. Color texture features extraction

In the image analysis, among most significant visual attributes one is color textures. The proposed color texture classification algorithm framework [38] was used in this work. Where, the proposed color monogenic wavelet transform (CMWT) was used in order to obtain color texture features. Let I be a color texture image with a size of W×H. Applying CMWT to I results in a decimal binary decomposition into l=1, 2, ... L scale, where the size of each scale is W/2l×H/2l. There is an amplitude (M(l)) and three phases (φ(l), θ(l), ϕ(l)). Then the decomposition coefficient of CMWT is expressed as Cl={M(l), φ(l), θ(l), ϕ(l)}. The average value S1(Cl), standard deviation S2(Cl), energy S3(Cl) and entropy S4(Cl) are defined as in (4)-(7):

$$S_1(C_l) = \frac{2^{2l}}{W*H} \sum_{x=1}^{W/_{2^l}} \sum_{y=1}^{H/_{2^l}} C_l(x,y) \quad (4)$$

$$S_2(C_l) = \sqrt{\frac{2^{2l}}{W*H} \sum_{x=1}^{W/_{2^l}} \sum_{y=1}^{H/_{2^l}} (C_l(x,y) - S_1(C_l))^2} \quad (5)$$

$$S_3(C_l) = \frac{2^{2l}}{W*H} \sum_{x=1}^{W/_{2^l}} \sum_{y=1}^{H/_{2^l}} |C_l(x,y)| \quad (6)$$

$$S_4(C_l) = \frac{2^{2l}}{W*H} \sum_{x=1}^{W/_{2^l}} \sum_{y=1}^{H/_{2^l}} [C_l(x,y) * log(C_l(x,y)^2] \quad (7)$$

Finally, for fish image's every color texture, CMWT sub-bands' few statistical characteristics features at various scales which are entropy, energy, standard deviation, and mean value were extracted.

3.4. Using anchor points to calculate shape features

In this work, a set of fish object anchor points (APs) will be defined to extract features. This is achieved using a geometric feature extraction technique. The anchor points must be manually defined for the mode of interest, and the positions of these anchor points are considered to be different points for geometric measurement (such as angle and distance), as shown in Figure 6. Where access points are identified and examples thereof, the beginning of the fish mouth, the dorsal fin, the beginning of the caudal fin, the center of the eye, and so on. 28 anchor points will be determined in this research work to extract the shape features.

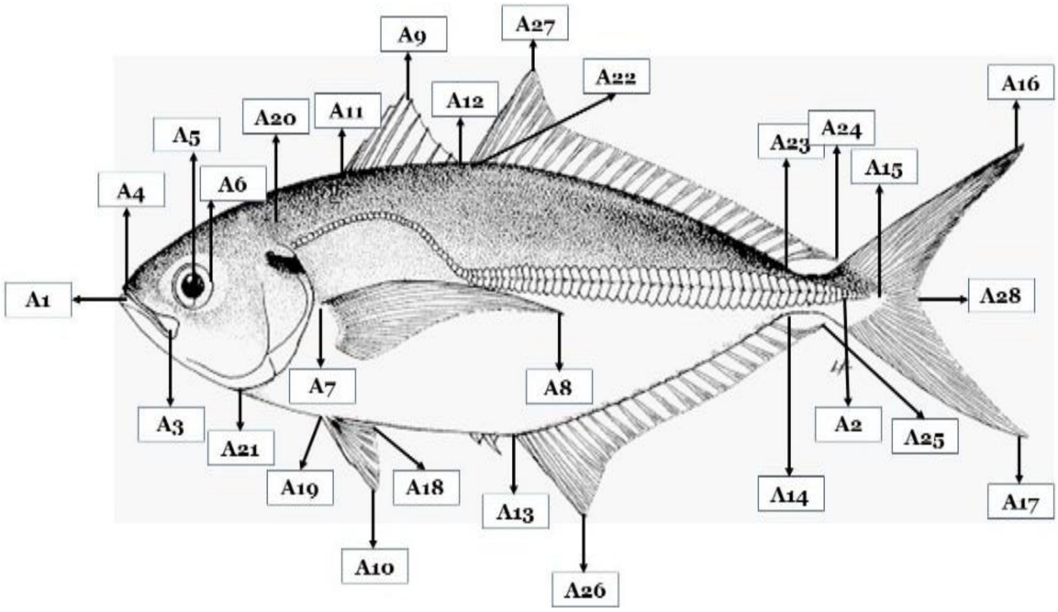


Figure 6. The locations of the anchor point measurements

The idea applied here is to make connection between different anchor points. Minimum and maximum points on x-axes with minimum and maximum points on y-axes to produce triangles that will be used in the feature's extraction process. To calculate the distance measurements, the 28 anchor points namely, A1, A2, A3, A4, A5, A6, A7, A8, A9, A10, A11, A12, A13, A14, A15, A18, A19, A20, A21, A22, A23, A24, A25, A26, A27 and A28 as shown in Figure 6. These anchor points are connected to produce 50 distances such as distance1 (A1-A15), distance2 (A28-A17) and distance3 (A25-A5). The distance 'D' between two points A (a_1, b_1) and B (a_2, b_2) is expressed in (8) [32].

$$D = \sqrt{(\Delta a)^2 + (\Delta b)^2} = \sqrt{(a_2 - a_1)^2 + (b_2 - b_1)^2} \quad (8)$$

The angle θ between two lines is calculated using the formula in (9) [35].

$$Cos\ \theta = \frac{|\bar{a}.\bar{b}|}{|\bar{a}|.|\bar{b}|} \qquad (9)$$

Moreover, 20 angle-based features were extracted to be used such as angle1 (A11, A15, and A21), angle2 (A1, A27, and A17) and angle3 (A1, A26, and A28).

3.5. The proposed classifier

In this work, the BP algorithmic program learns the multi-layer feedforward neural network [39]-[41]. The BP algorithmic program iteratively learns the weight set to predict the category label of the tuple. The multi-layer feedforward NN consists of 3 layers, that area unit input layer, hidden layer and output layer. The number of neurons in every layer is totally different. The number of neurons in the input layer can represent the number of extraction options, the hidden layer has 45 neurons, and the range of neurons in the output layer can form a family (24 in total). Supports options extracted from color texture, color features and shape metrics, and uses BP algorithm programs to guide, observe and classify fish families. Figure 7 shows the multi-layer feedforward NN consists of 3 layers.

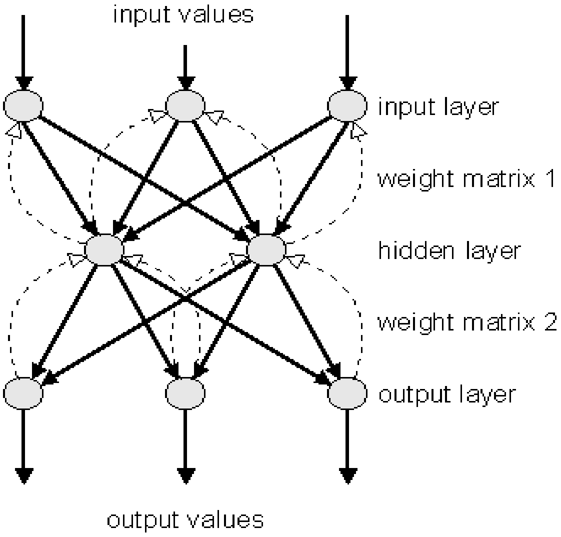


Figure 7. Multi-layer feedforward NN consists of 3 layers

3.5.1. Metaheuristic algorithm

In this work, a hybrid genetic algorithm that integrates the SA algorithm is used to adjust and optimize the weights of the BP algorithm, and a meta-heuristic search technique is used to deal with the main limitations of BP, such as slow convergence [42]-[44]. Figure 8 illustrates the flow chart of the proposed GSB classifier. The SA algorithm is inserted in GA to improve the development process instead of the exploration process [45]-[48]. Table 1 shows the parameter settings of the proposed algorithm.

The proposed hybrid algorithm phases are as follows:

- Initialization: Utilize twofold numbers to address every arrangement in the pursuit space. The genuine worth (score) is utilized to address the chromosomes in the weight grid.
- Selection: To create another arrangement with a higher wellness esteem, select the chromosome with the most elevated wellness worth to imitate in the populace space. In this examination, roulette choice is utilized as the determination instrument.
- Crossover: Cross joining the chromosome data of the two guardians, and make another youngster chromosome, that contains part of each parent hereditary material.
- Mutation: Change is completed by getting a parent chromosome, and arbitrarily making kid chromosomes by trading certain pieces in the parent chromosome.
- Fitness function: It assesses the nature of up-and-comer arrangements as per the difficult area. This examination utilizes the change record capacity (VAF), which is calculated as in (10) [28]:

$$V = 1 - \frac{variance(y - y_{test})}{variance(y)} \qquad (10)$$

The genuine output is indicated as y, y-test is the output of the model assessment, and to acquire the output V, by contrasting the normal model output and the real output, VAF is determined for the two signs utilized for model rightness assessment.

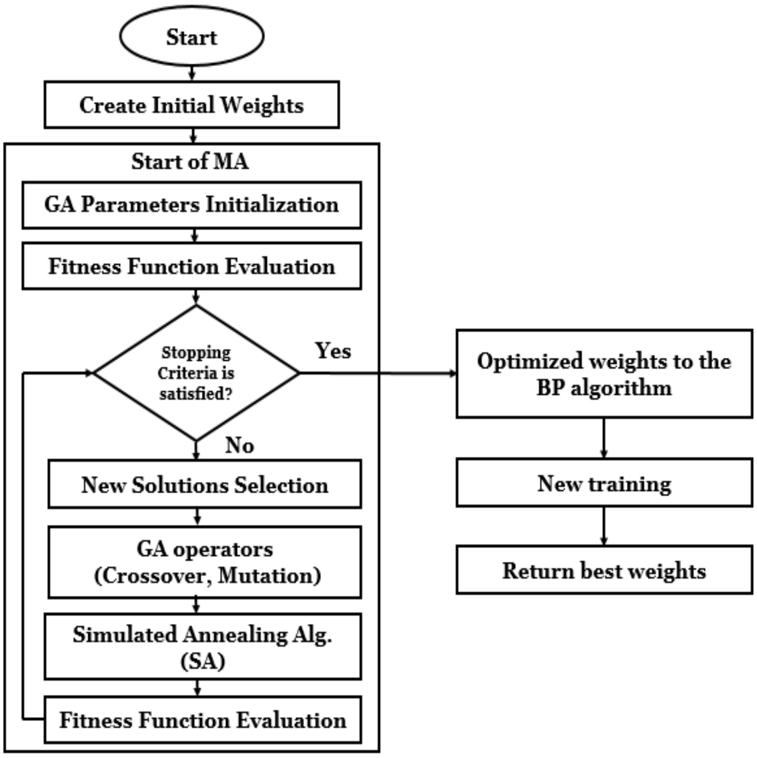


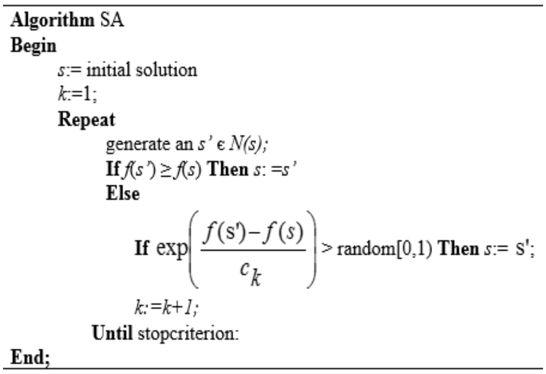
Figure 8. The diagram proposed GSB classifier

3.5.2. Simulated annealing algorithm

The SA algorithm is started after completing the selection and GA operators (crossover and mutation. Generally, Kirkpatrick in (1983) SA is a stochastic algorithm. It tries preventing falling into local optima by allocating probabilities for failing movements [49]. Contrary to a simple local search, SA seems to have a greater function, because a worse solution with few possibilities is also accepted [44], [50], [51]. SA has been utilized by various people to solve difficult problems. For the SA algorithm, the cooling process is critical. The choice of temperature (ck) value depends on the cooling method. The cooling method involves setting the temperature constant for several generations before lowering the temperature. Since SA contains a random algorithm that attempts to prevent falling into a local optimal solution by assigning probabilities to deteriorating movements, the solution acceptable to SA is not better than the previous solutions, but it is not much worse. Therefore, the solution can get rid of the local optimal and find the global optimal solution [52], [53].

For the maximization problem, Figure 9 provide a general SA algorithm. From the overall population in GA, SA must first select the best weight solution. Initially, the starting and the final temperature are set to 1000 and 0, respectively. At the same time, the iteration amount #Iter is 300. In the iteration, the temperature is randomly reduced by creating a score between 0 and 1. Then, redefine the neighbors by randomly creating a random score between 0 and 1 added to the solution. Use the formula represented by equation (3) to calculate the new neighbor's fitness function value. If the number create at random is less than e-δ/T, wherein δ=f(s')-f(s), and T=ck(ck) presents the current iteration number temperature, a worse solution can be adopted. The current solution has been updated. Till the maximum iterations number is reached, specifically 600 iterations, this process continues.

Here, the metaheuristic algorithm proposed is easy to accept a solution with greater applicability. At the same time, if a solution with a fitness value similar to that of the best solution has fewer matching features, they will be accepted. Table 1 presents the proposed MA's parameter settings. Figure 10 represents the proposed MA's pseudo code.

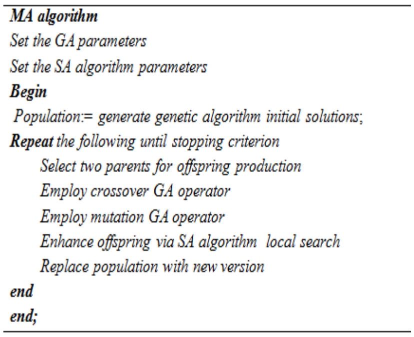


```
Algorithm SA
Begin
    s:= initial solution
    k:=1;
    Repeat
        generate an s' ∈ N(s);
        If f(s') ≥ f(s) Then s: =s'
        Else
            If $\exp\left(\frac{f(s')-f(s)}{c_k}\right)$ > random[0,1) Then s:= s';
            k:=k+1;
    Until stopcriterion:
End;
```

Figure 9. A SA algorithm [50]

Table 1. Metaheuristic algorithm parameters setting

Parameter	Value
Final temperature	0
SA generation number	300
Initial temperature	1000
GA Iterations number	900
Rate of mutation	0.02
Rate of crossover	0.90



```
MA algorithm
Set the GA parameters
Set the SA algorithm parameters
Begin
 Population:= generate genetic algorithm initial solutions;
Repeat the following until stopping criterion
    Select two parents for offspring production
    Employ crossover GA operator
    Employ mutation GA operator
    Enhance offspring via SA algorithm  local search
    Replace population with new version
end
end;
```

Figure 10. Pseudo code of the MA algorithm [54]

4. RESULTS AND DISCUSSION

Table 2 shows the quantity of highlights extricated utilizing the proposed feature extraction strategy, of which 9 are color highlights utilizing color moments and ranklet transform methods, 4 are color surface highlights utilizing CMWT method, and 70 are shape highlights utilizing geometrical measurements. In this work, the extracted shape features are limited to 25 features to decide the powerful features in the removed features, which will assist with acquiring higher grouping precision. Minimization of features has been accomplished utilizing the representation apparatuses gave in Weka arrangement programming.

In the proposed classifier, the way toward utilizing MA and BP calculations for boundary learning incorporates two stages. The first is: The weight at first got by NN is advanced and upgraded using the proposed MA. The proposed MA is upgraded and expanded by the wellness number to improve constantly the weight acquired (arrangement quality). Besides, BP calculation is utilized to prepare the loads upgraded by MA. Table 3 shows the general arrangement exactness aftereffects of the customary BP calculation and the proposed cross breed GSB calculation.

Table 2. Extracted features number

Methods	Extracted features number	Extracted features number after Selection
Color features	27	18
Color texture features	4	4
Shape features	70	25

Table 3. Overall classification accuracy results

Algorithm	Classification accuracy
BP	82.9%
Proposed GSB	87.7%

As demonstrated in Figures 11, 12 and 13, contrasted and other ongoing techniques, for example [34], the proposed half breed GSB classifier performs better as far as speed and characterization exactness. The fish declaration and the general changes in the fish objects presence inside the picture have little impact on the shading mark and highlights. Thusly, as demonstrated in Figures 11 and 12, the best precision results for the BP and GSB classifiers are 87% and 92%, separately, while the most noticeably terrible outcomes are 81% and 85%, individually. In light of the extricated features. SA with GA incredibly improves the acknowledgment exactness of BP by upgrading and streamlining the loads utilized in BP preparing and testing.

As opposed to ordinary strategies, the proposed include extraction technique and classifier show preferred execution over the current techniques utilized in [34], particularly as far as generally speaking grouping exactness, as demonstrated in Figure 13 with a level of 82.9 and 87.7. The outflow of the color fish and the worldwide difference in the fish object in the image appear to have less effect on the color surface estimation.

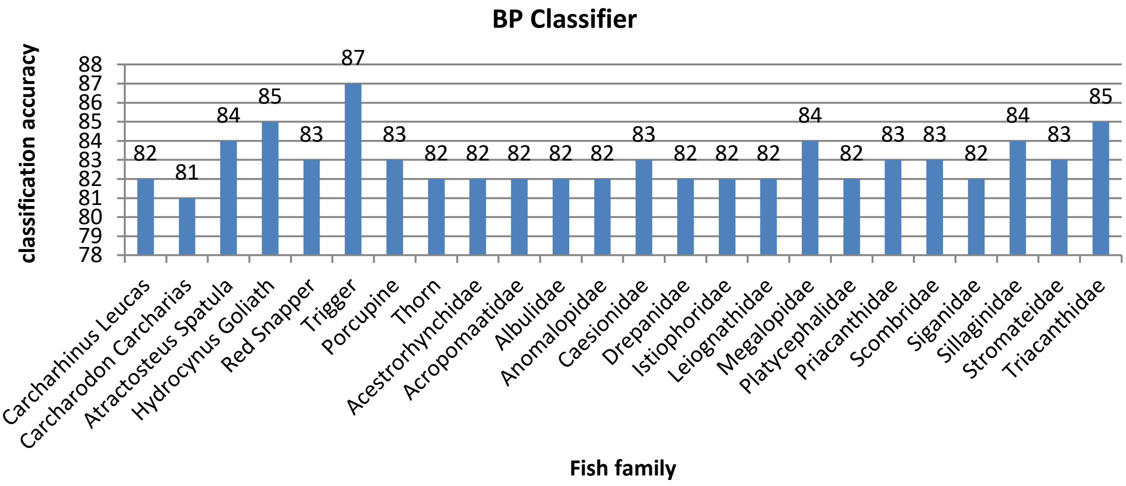


Figure 11. Classification accuracy results using BP classifier

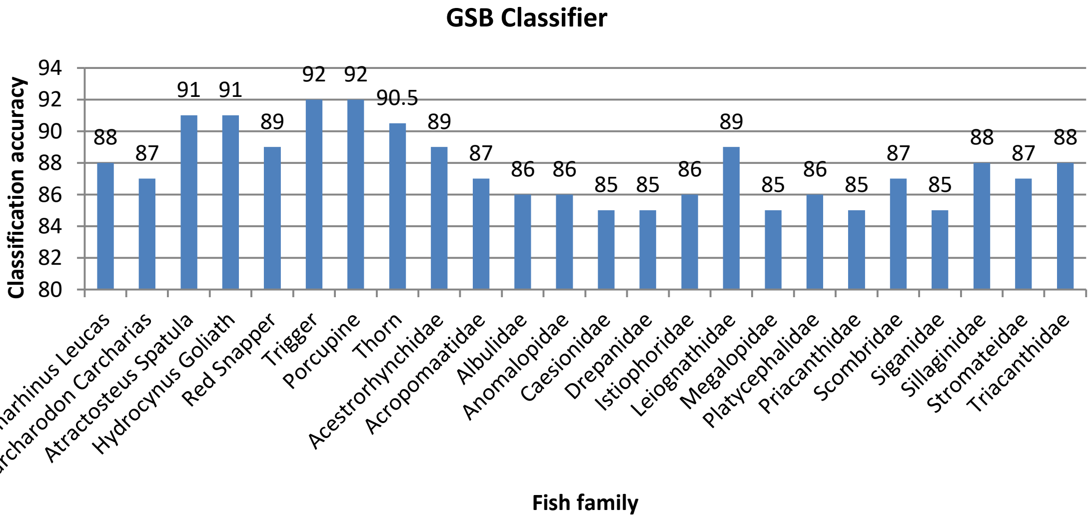


Figure 12. Classification accuracy results using GSB classifier

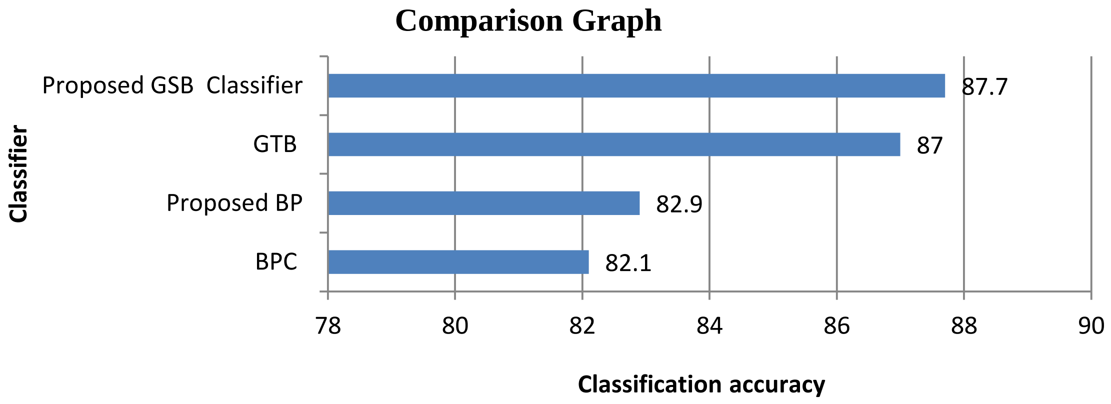


Figure 13. The comparison between the proposed (GSB and BP) and the other methods (GTP and BPC) in [34]

Furthermore, contrasted and the customary BP classifier, the GSB classifier shows better execution. Furthermore, to confirm the consequences of the proposed GSB classifier execution all the more successfully, the GSB classifier is contrasted and other classifier strategies utilizing a similar informational index (separated highlights) for reasonable correlation. The technique picked for examination in this investigation is the radial basis function (RBF) network that is executed by "*Weka classification software*". It has been shown by Table 4 that the RBF network acquires a higher classification rate that is near that of the BP classifier. Notwithstanding, contrasted and the RBF network, the BP classifier gets better arrangement results. Then again, the got results show that the proposed crossover GSB classifier is altogether better compared to the RBF network, as demonstrated in the accompanying table.

Table 4. General classification results for the RBF network and proposed classifiers

Classifier	BP	Proposed GSB	RBF network
Classification accuracy	82.9%	87.7%	82%

5. CONCLUSION

In this article, we present a fish image classification dependent on color highlight, color surface and shape include extraction. The mix of color highlights separated utilizing color moments, and shape highlights removed utilizing point and distance estimations are utilized to extricate powerful fish classification features. In this work, learning the boundaries of the MA and BP calculation measure incorporates two stages. The first is: the artificial neural network advances and improves the underlying loads. The BP calculation is utilized to train the weights improved by MA. The BP and GSB mixture classifiers show preferable execution over the most recent strategies, with grouping precision of 82.9% and 87.7%, individually, and effectively arrange fish images as predatory, poisonous, garden and edible fish.

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