# The LETBP feature descriptor based fish species classification using Kepler optimization with Extreme Learning Machine

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**Abstract:** Fish species classification plays a crucial role in underwater environments, serving to audit ecological balance, monitor fish populations, and preserve endangered species. However, the interaction of light with ocean water results in scattered and absorbed light, leading to hazy, low-contrast and low-resolution images. This, in turn, makes fish classification a challenging and arduous task. Hence, in order to address the issue in this paper an automatic fish classification technique is proposed. To improve the quality of the images a basic CLAHE image enhancement technique is applied. Then, the novel feature descriptor method called local energy triangular binary pattern (LETBP) is proposed to extract features from the images, which effectively extracts the pixel information from all directions. The extracted unique feature values are given to the Extreme Learning Machine (ELM) for the final classification. The ELM network randomly selects the bias and weights and in order to overcome this issue an optimization technique called Kepler Optimization Algorithm (KOA) is adopted. The KOA algorithm tries to improve the search space of exploration and exploitation ratio. The augmented dataset is given to ELM classifier for the classification fish species. The proposed KOA-ELM achieves the high classification rate of 99.23 on fish (F4K) dataset.

**Keywords:** Feature Descriptor, Fish classification, Optimization Algorithm, ELM Classifier.

## 1. Introduction

The defaunation is well advanced in freshwater and terrestrial environments where it basically started a few centuries ago. However, the arrival of industrial fishing is primarily responsible for the acceleration of defaunation in oceans. The management of fisheries depends on an accurate stock assessment, particularly in light of the growing global demand for fish. It is difficult to observe and research ecological processes in this ecosystem since it is so dynamic and very complicated. In fact, the labor-intensive process of manually extracting information on fish biodiversity and abundance from unprocessed videos requires highly qualified taxonomic specialists. Indeed, manual annotation of fish species classification is time consuming and increases the workload for large datasets. Fish species classification by humans is completely impractical in real-world applications since it frequently requires significant financial expenses and is vulnerable to human error. To overcome the problem with human categorization, automatic annotation systems have been recently proposed. The vision based automatic system should have the following feature conditions:

- Random scale and orientation: Fish can be found in a wide range of sizes, positions, and body types;
- Environmental condition: the illumination and water transparency are different for all locations;
- Failures in segmentation: It may not be accurate to segment a certain fish;
- Image quality: the underwater images are typically affected by noise and distortion.

Prasenan & Suriyakala (2022) have introduced the technique for the classification of fishes.

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The morphological operations are performed to have unique feature value to improve the performance. Next, the firefly optimization algorithm is applied to select the region of interest. Finally, the custom model named PatternNet is applied to classify the images. Prasenan and Suriyakala (2023) have implemented Modified Convolution Neural Network (MCNN) for fish species classification. In this new preprocessing, a methodology called thinning is used along with the hit miss function to improve the image quality. The Hadamard Control Firefly Algorithm (HCFA) is applied over an image data set to separate the features of the images. This helps to improve the classification accuracy. The proposed method validated over 2000 images belonging to 5 internal categories. The system achieved a 97.55% classification accuracy. Iqbal et al. (2021) developed a deep learning model to classify fish species. The proposed system comprises the basic version of AlexNet model which includes two fully connected layers and four convolution layers. To evaluate the performance of the classification model it was compared with another existing technique called VGGNet. The parameters were finely tuned to achieve a higher classification accuracy on the training dataset. The modified AlexNet with a smaller number of layers proved to be able to achieve a 90.48% classification accuracy whereas the original AlexNet model was able to achieve only 86.65%. Rodrigues et al. (2015) also developed a feature descriptor for the classification of fish species., Three feature descriptors like SIFT, PCA and SIFT+VLAD+PCA were used to extract features followed by clustering techniques like AiNet, K-means and ARIA to classify them. The proposed method is compared with the existing classifiers like KNN, SIFT etc., Li et al. (2022) proposing a fusion technique model Tripmix-Net which combines both multilayer and residual neural network. The experiments validated using 15 categories of wild fish dataset for classifying same- fishes with complex backgrounds. The model achieves a higher classification accuracy of 95.31%. Mana & Sasipraba (2022) proposed a fish classification model named intelligent deep learning based marine species classification. Primarily, the images are pre-processed using Weiner filter to remove unwanted noise. Next, Mask R-CNN with Residual network is used to detect the fish. The proposed technique achieves the classification accuracy of 98.03%. Haugen (2023) proposed a pre trained CNN as a cross-layer feature descriptor reaching an accuracy of 94.3% for fish species from typical underwater video imagery captured off the coast of Western Australia.

In this paper the automatic fish classification system proposed uses ELM classifier. The purpose is to evaluate and determine the best method for the given datasets. After extracting the feature, the extracted values are imported to ELM classifier for the final classification.

The existing techniques like back propagation and gradient decent methods depend on parameters like initialization approach and feature space, so there is a greater chance that they will converge at a local end. Hence, in order to overcome the above drawbacks, an ELM classifier is introduced. The ELM classifier is a single layer feeding forward the neural network which assigns the input weight and biases randomly. The coverage rate of the ELM is much faster than that of the other existing techniques. The universal approximation ability is guaranteed by random concealed nodes. Thus, the ELM technique can reach the global optimal solutions better than the other existing techniques. Because of the random initialization of parameters, the ELM model requires a greater number of hidden neurons and this introduces the problem of ill condition and overfitting. In order to overcome these problems in ELM classifier, this is combined with the optimization technique to improve the performance of the classifier.

The structural flow of the papers is described in Figure1. The related work is presented in Section 2 and the proposed feature extraction method is given Section 3; the datasets used for the evaluation of the proposed scheme are presented in Section 4 and the results and discussion are reported in Section 5.

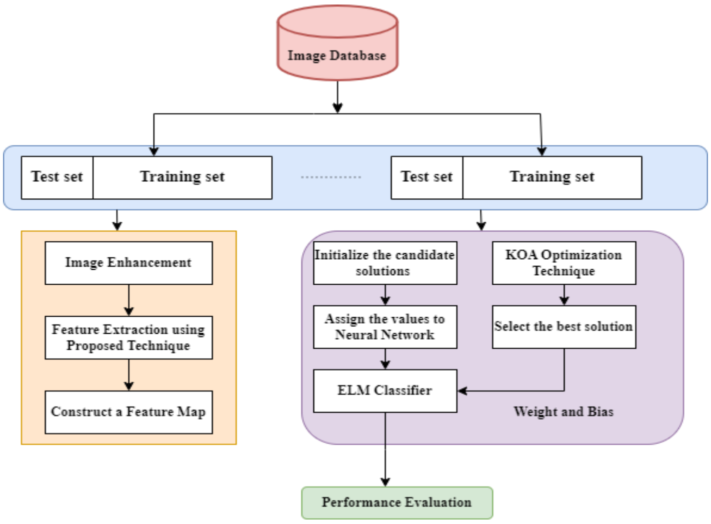


**Figure 1.** Flow Diagram of Proposed Model

## 2. Proposed feature descriptor

The author proposed a novel texture descriptor method based on the pixels difference between the ternary sequence. To capture the unique feature value mutual information and multi degree schemes were used. To reduce the dimensions of the feature the Min Redundancy Mutual Information (UMRMI) technique is proposed as feature selection technique for the optimal feature value. Agarwal et.al. (2021) proposed the local binary hexagonal extrema pattern (LBHXEP) to extract feature information from hexa neighbours and center pixels. To extract the information from all the directions the hexagonal shape based on six neighbourhood approaches is proposed, which brings a more efficient and higher symmetry when compared with the existing techniques. The hexagonal method is based on the concept of honey comb, making an effective use of the space and producing a higher resolution with a solid structure. The proposed hexagonal technique achieves a higher classification rate of 98.3 on IRIS dataset. Chakraborti et al. (2018) proposed the Local Optimal Orientation Pattern (LOOP) descriptor to overcome the drawback of traditional methods like LBP and LDP technique. It consisted of applying the directional kirsch mask over the image to extract unique directional information, then assigning the binary weights to the directional values to extract unique kirsch mask value. Hence the LOOP method incorporates the advantages of both LBP and LDP methods. Kartheek (2021) presented the work based on the three-descriptor technique for extracting the unique discriminant features namely Radial Cross Pattern (RCP), radial cross symmetric pattern (RCSP) and Chess symmetric Pattern (CSP). The feature is extracted using the 5×5 overloop matrix. The 24-pixel surrounded by the center pixels are distributed to form two groups. The RCP method extracts two discriminate values by comparing 16 pixels with the center pixels. The CSP method extracts one feature value by comparing the remaining 8 pixels. These proposed feature descriptors and the fusion of these two methods, namely RCSP, are evaluated by using the facial expression dataset. Kas et al. (2020) presented the Multi-Level Directional Cross Binary Patterns (MLD-CBP) as having a low dimensional, unique robust texture descriptor. The MLD-CBP extracts the multi directional information from the images. The information is extracted from 5 × 5 gray scale images, to show the micro pattern deviation in the particular images. The proposed technique incorporates both the directional and radius concepts and makes the feature more obviously unique. Roy et al. (2020) developed the second order gaussian derivative filter-based texture descriptor called local jet vector (LJV). The gaussian derivative filter retains the local structure information which makes the descriptor vary with rotation, scale and reflection. Arya & Vimina (2023) proposed the local energy triangular binary pattern (LETBP) which extracts the pixel information in triangular pattern by considering multiple center pixels. Compared with the traditional technique, the proposed LTCP has unique feature values because instead of comparing the single pixel with the neighbourhood pixel, the two pixels are compared with the center pixels. Finally, the features make a unique 8-bit binary value.

In order to overcome the shortcomings of the existing feature descriptors, a novel feature descriptor is proposed to extract the unique feature value. In traditional LBP (Ojala et al. 1996) method the center pixel is considered the threshold value and compared with the surrounding pixels, whereas in the proposed technique method it is modified by taking the average of the surrounding pixels and re-placing it as a center pixel. This brings the strong discriminant value to the descriptor. To further improve the performance of the proposed system, directional information is also included. The existing local directional pattern (LDP) includes the kirsch mask to extract information from all eight directions. The dominant values are selected as a feature point but the center pixel values are not taken into consideration (Jabid et al., 2010). To overcome this issue, a novel descriptor is proposed, known as local triangular energy orientation by pattern (LTEOBP). In this descriptor two triangular patterns are considered like 60 degree and 180 flip. The 60-degree triangular $C_c$ is considered the center point for the remaining three pixels. Then the angle is set for 180° and the same process is repeated for the other set of values, as presented in Figure 2.

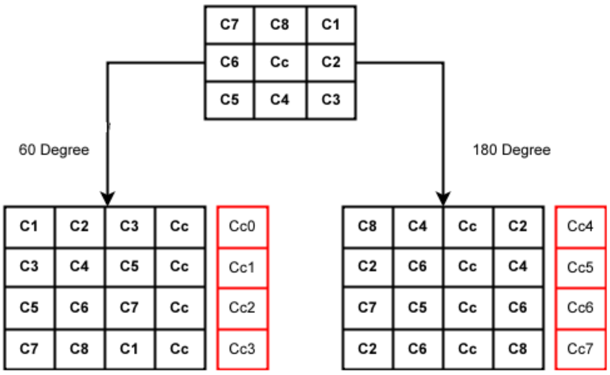


**Figure 2.** Proposed LETBP Technique Workflow

The procedural steps for the implementation of the proposed descriptor are as follows:

1. Convert the image into gray scale image, consider the 3 × 3 intensity matrix value take average and replace the value as center pixel ($C_c$) value using the following equation

$$C_c = Avg \tag{1}$$

2. Like in the traditional LBP method, the new $C_c$ value is compared with the neighbourhood pixels, and, if the neighbourhood pixels value is higher than the threshold value, then the binary value 1 is assigned or otherwise 0 is assigned.

3. After processing all that the final 8-bit value is formed. This new image is called a Boosted intensity image (BII).

Next, it is necessary to incorporate the directional information the 3 × 3 intensity matrix value. To extract the edge information effectively, the 60° triangle is formed in all the four directions.

4. Each triangle covers four-pixel information, and the center pixel value is taken as a threshold value for the other three pixels. If the two neighbour pixel values are higher than the center pixel then the value 1 is assigned, otherwise 0 is considered.

5. If $C_{c0}$ is the output for any one direction which contains four elements in the matrix $C_1, C_2, C_3$ and $C_c$ then $C_c$ is considered as a threshold for all the three remaining values. If $C_c$ is higher than any of the two neighbouring pixels, then the value 1 is assigned, otherwise 0 binary value is generated.

$$C_{c0} = binary(\max[C_1 - C_c],[C_2 - C_c],[C_3 - C_3] \tag{2}$$

$$C_{c1} = binary(\max[C_7 - C_6],[C_5 - C_6],[C_c - C_6] \tag{3}$$

$$C_{c2} = binary(\max[C_7 - C_6],[C_5 - C_6],[C_c - C_6] \tag{4}$$

$$C_{c3} = binary(\max[C_7 - C_6],[C_5 - C_6],[C_6 - C_8] \tag{5}$$

6. After computing the four directional information, the angle is set to 180°. The process is repeated like in the previous procedure. For example, the $C_C$ binary value is obtained $b$ comparing the $C_4$ , $C_8$ , $C_2$ and $C_c$ . Here $C_2$ is considered the center pixel and compared with the neighbouring pixels. If the center pixel value is higher than any of the two neighbouring pixels, then value 1 is assigned, otherwise 0 binary value is generated.

$$C_{c4} = binary(\max[C_8 - C_2],[C_4 - C_2],[C_c - C_2]) \tag{6}$$

$$C_{c5} = binary(\max[C_2 - C_4],[C_6 - C_4],[C_c - C_4]) \tag{7}$$

$$C_{c6} = binary(\max[C_7 - C_6],[C_5 - C_6],[C_c - C_6]) \tag{8}$$

$$C_{c7} = binary(\max[C_2 - C_8],[C_c - C_8],[C_6 - C_8]) \tag{9}$$

7. After that the eight-code directional information is obtained using the following

$$C_{cp} = \sum_{i=0}^{n} b(p_i - C) \geq \frac{n+1}{2} \tag{10}$$

$$LDEP(X_c, Y_c) = \sum_{n=0}^{7} T(C_{cp} - C)2^n \tag{11}$$

$$Thr(v) = \begin{cases} 1 & if \;\; v \geq 0 \\ 0 & otherwise \end{cases} \tag{12}$$

8. Finally, both BII and LEDP binary values are concatenated using the following condition

$$Int[BII(P_i), LEDP(P_i) = \begin{cases} 1 & BII \neq LEDP \\ 0 & BII = LEDP \end{cases} \tag{13}$$

The proposed technique steps are elaborated in Figure 3.

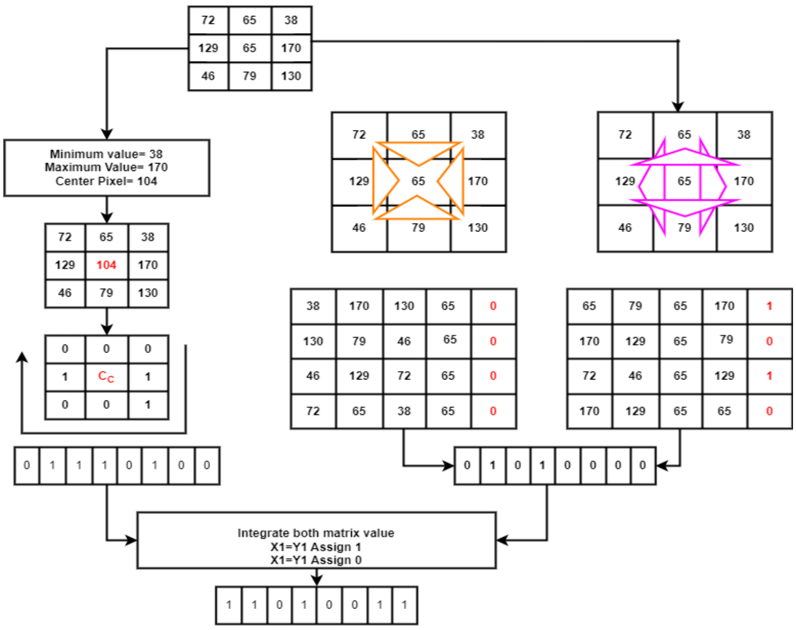


**Figure 3.** Proposed LETBP Technique Image Representation

After extracting the image feature, the next step is the classification. To classify images, this paper has adopted an Extreme Learning Machine (ELM) d. Huang, G.B (2011) proposed an ELM as an effective feedforward neural network. The traditional algorithm requires an increased number of parameters to train the neural network, which also overcomes the problem of the local optima. In ELM classifier the hidden layer used to fine to the parameters of ELM without changing the weight and bias value. The ELM network randomly selects the weight to the hidden layer. The ELM contains n number of input layer, L hidden layer and m number of output layers. The ELM model is derived based on the following

$$\begin{cases} M(X_i) = \sum_{i=1}^{L} \beta_{ik} R_{ik}(X_j) = R(X_j) = R(X_j)\beta \\ N(X_i) = r_i(\omega_i X_i + b_i) \end{cases} \tag{14}$$

where $\beta = [\beta_1, \beta_2, \beta_3, ....\beta_L]^T$ is the weight matrix created based on the output layer and the hidden layer. The activation function is noted as $R(.)$, the weight function is noted as $\omega_i$ between the input layer and hidden layer, $b_i$ is the bias on the network. Once the weight $\omega = [\omega_1, \omega_2, \omega_3, .....\omega_L] \in G^{n\times L}$ and the biase $b = [b_1, b_2, b_3, .....b_L] \in G^{L\times L}$ are randomly initiated, the hidden nodes values are calculated by using the following

$$H = \begin{cases} R(X_1) \\ \vdots \\ R(X_n) \end{cases} \tag{15}$$

$$H = \begin{bmatrix} r_1(\omega_1{}^T X_1 + b_1) r_1(\omega_1{}^T X_1 + b_1) \cdots r_1(\omega_1{}^T X_1 + b_L) \\ r_1(\omega_1{}^T X_2 + b_1) r_1(\omega_1{}^T X_2 + b_1) \cdots r_1(\omega_1{}^T X_2 + b_L) \\ \vdots \qquad \vdots \qquad \ddots \qquad \vdots \\ r_1(\omega_1{}^T X_n + b_1) r_1(\omega_1{}^T X_n + b_1) \cdots r_1(\omega_1{}^T X_n + b_L) \end{bmatrix} \tag{16}$$

The training error can be minimized by using the following

$$\min \| H\beta - y_i \| \tag{17}$$

where $y_i = y_1, y_2, y_{3\cdots} y_m \in R^{d\times m}$ is the target matrix and $d$ is the number class present in the output layer. The optimal solution for the β is expressed by

$$\hat{\beta} = H^{\dagger} Y \tag{18}$$

where $H^{\dagger}$ is the moore penrose inverse matrix of H. However, the traditional ELM randomly selects the weight and biases in the network. This leads to the problem of the local optima. Therefore, in this paper, a hybrid technique has been adopted, to combine ELM with the optimization technique. Thus, Kepler's optimization algorithm has been used to optimize the weights and biases of the ELM classifier.

## 2.1. Kepler's Optimization Algorithm (KOA)

To optimize the parameters of the ELM classifier a new technique called Kepler's optimization algorithm (KOA) has been adopted by Abdel-Basset et.al. (2023). he KOA technique is innovating being inspired by Kepler's law of motion. Kepler's law accurately predicts the position and velocity of the plants at all time. In KOA algorithm, each position of the plant is considered as a candidate solution to continuously optimize the process and try to achieve the best solution (Sun). That means the KOA algorithm tries to improve the exploration and exploitation ratio to achieve a good candidate solution from the Sun at different times. The traditional method has the problem of several drawbacks like the local optima, the lower coverage speed and lacks in the population variations. To overcome the issues this KOA provides new and independent solutions to solve the continuous optimization problems. The KOA technique works based on the four fundamental operations of position, gravitational force, mass and velocity. All the planets around the sun can be considered as a candidate solution, which creates the relationships with the Sun at different periods providing wide search space in exploration and exploitation.

The KOA algorithm is used to obtain the search space by considering the Sun as the center and the planets revolving around it on their orbital paths. The best candidate solution is obtained by making the search space to explore different situations at different times. First, each orbit is assigned to a random position. Once it determines the starting point it continuous this procedure till the termination. The KOA extracts the optimal value by considering the following rules:

- The normal distribution is used to select the candidate solution at random;
- The eccentricity value ranges from 0 to 1;
- The fitness is evaluated by considering the objective functions;
- The Sun is considered an optimal solution center star;
- The distance between the Sun and the planets will change according to the time.

In KOA technique the N refers to the number of planets which is equal to the population size. In KOA the search space values are randomly selected with respect to the optimization problem according to

$$X_m^n = X_{m,low}^n + rand_{(0,1)} \times \left| X_{m,upper}^n - X_{m,lower}^n \right| \tag{19}$$

d- stands for the dimension of the problem m, $X_{m,upper}^n$ and $X_{m,lower}^n$ note the lower and upper bound, $rand_{(0,1)}$ denotes the number generated randomly between 0 and 1. Each m$^{th}$ object's orbital eccentricity (e) is set using

$$e_m = rand_{(0,1)}, m = 1, 2 \cdots N \tag{20}$$

where $rand_{(0,1)}$ is generated randomly within the interval [0,1]. Finally, for each m$^{th}$ object, the orbital period (T) is calculated with

$$T_m = |r|, m = 1, 2, \cdots N \tag{21}$$

where $r$ is generated randomly by using a normal distribution.

## 2.2. Gravitational force

Gravity is the main factor enabling the planets to rotate around the Sun. The gravity of any planet will vary according to its size. Each planet experiences variations in velocity due to the Sun's gravitational pull. On the other way, the planets with higher orbital velocities will be nearer to the Sun. The value of the attraction force $X_S$ and $X_p$ will be decided by the law of gravitation:

$$F_{grav}(t) = e_p \times \mu_s \times \frac{Q_s \times q_p}{R_i^2 + \varepsilon} + r_1 \tag{22}$$

where $Q_s$ and $q_p$ is the mass value of the $X_S$ and $X_p$ respectively, $e_p$ is the eccentricity of the planet $r_1$, $\varepsilon$ is the small value, $\mu_s$ is the gravitational constant, $R_i^2$ is the euclidean distance between the $X_S$ and $X_p$. Hence $\left\| X_s(t) - X_p(t) \right\|_2$ represents the Euclidean distance between $X_s$ and $X_p$ the dimensions

$$R_i(t) = \left\| X_s(t) - X_p(t) \right\|_2 = \sqrt{\sum_{i=1}^{N} (X_s(t) - X_p(t))^2} \tag{23}$$

$$Q_s = \frac{fit_s(t) - worst(t)}{\sum_{k-1}^{N} fit_s(t) - worst(t)} \tag{24}$$

$$Q_s = \frac{fit_p(t) - worst(t)}{\sum_{k-1}^{N} fit_p(t) - worst(t)} \tag{25}$$

$$\mu(t) = \mu_0 \times \exp\left(-\gamma \frac{t}{T_{\max}}\right) \tag{26}$$

where $\gamma$ is the constant, $\mu_0$ is the initial value, $T_{\max}$ represents the maximum number of iterations and t is the current iteration.

## 2.3. Object velocity calculation

The velocity of a planet is determined by its position with respect to the Sun. The velocity of each planet increases when it reaches a position close to the Sun and reduces when its moves away from the Sun. When the planet comes close to Sun, the gravitational power of the letter tries to pull it towards the Sun. Then the two-fold equation is used to calculate the velocity of the planet. The first fold velocity is calculated by multiplying both random and current solutions regarding the distance. This helps to expand the search space solutions, by minimizing the velocity of the planet which is closer to the Sun. In the second fold the velocity is computed based on the assumed distance between the present and the random values associated with the first fold able to lessen the velocity of the planet. That results in a lack of diversity, due to the KOA being affected by the local optima. To overcome this issue the second fold follows some other strategy to reduce the distance between the lower and the upper bound

$$V_i(t) = \{ l \times (2r_4 \bar{X}_i - \bar{X}_b)_2 + \bar{l}\,(X_y - X_z) + (1 - R_{i-norm}(t) \times F \times \bar{U}_1 \times (X_{i,upper} - X_{i,lower}) \;\; if \;\; R_{i-norm} \le 0.5 \tag{27}$$

$$l = \bar{U} \times M \times L \tag{28}$$

$$L = \left[ \mu(t) \times (M_s + m_i) \left[ \frac{2}{R_i(t) + \varepsilon} - \frac{1}{a_i(t) + \varepsilon} \right] \right]^{1/2} \tag{29}$$

$$M = (r_3 \times (1 - r_4) + r_4) \tag{30}$$

$$\bar{U} = \begin{cases} 0 & r_5 \le r_6 \\ 1 & else \end{cases} \tag{31}$$

$$i = (1 - U) \times \vec{M} \times L \tag{32}$$

$$\vec{M} = r_3 \times (1 - r_5) + r_6 \tag{33}$$

where $V_i(t)$ represents the velocity of the object, $r_3$ and $r_4$ are random numbers generated between the interval [0,1], $\bar{X}_i$ represents the object $i$, $r_5$ and $r_6$ are two vector values ranging from 0 to 1, $X_a$ and $X_b$ denote the random values assigned from the population, $M_s$ and $m_i$ represent the mass value of $X_s$ and $X_p$ $Xp$ respectively. The variable $a_i(t)$ is the value of $i$ at time $t$.

$$a_i(t) = r_3 \times \left[ \frac{\mu(t) \times (M_s + m_i)}{4\pi^2} \right] \tag{34}$$

where $T_i$ symbolizes the orbital period of the object $i$. The value of the oblique major axis is set to decrease to achieve global best solution. $R_{i-norm}$ is the Euclidian distance between $X_s$ and $X_p$.

$$R_{i-norm} = \frac{R_i(t) - \min R(t)}{\max R(t) - \min R(t)} \tag{35}$$

The value of $R_{i-norm} \leq 0.5$ then, when the planets are close to the Sun, the speed is increased to avoid drifting towards it due to the Sun's immense gravitational influence.

## 2.4. Avoid the local optimum

Most of the planets around the Sun will rotate in anticlock wise direction, since only certain things revolve in clockwise direction. Hence the KOA uses this technique to avoid the local optima. In order to adopt this strategy, the flag F technique is used to give fair chance to all planets to get accurate search space.

## 2.5. Updating the position of the object

To change the position of the planet, the KOA method uses the exploration and exploitation stage. The KOA identifies the new solution for the things which are far away from the Sun by utilizing the nearby solutions for those which are closer to the Sun. In the exploration stage the efficient search space values are identified by moving the objects away from the Sun. The new position is changed by using the following:

$$X_i(t+1) = X_i(t) + F \times V_i(t) + \left(F_{gi}(t) + |r|\right) \times \bar{U} \times \left(X_5(t) - X_i(t)\right) \tag{36}$$

where $X_i(t+1)$ is the updated position of the object $I$ and at time with respect to the time $t+1$, $V_i(t)$ is the velocity of the object, $X_s(t)$ is the determines the best position of the Sun, $F$ is used to change the direction of the search space. However, the velocity of the planets being affected by the Sun's gravitational force allows to get the best solution for the current planet.

## 2.6. Updating the position with sun

To further enhance the ratio of exploration to exploitation, the typical behaviour of the planets and the Sun distance is adopted which varies over a period of time. When the planets approach the Sun in a tight orbit, the KOA will make a decision based on the priority. The variable parameter h applies a regularization to these ratios. When the value of h is high, the distance from the Sun to the planet grows with the exploration ratio. When h is small the exploration ratio revolves around the best solution.

$$X_i(t+1) = X_i(t) + \bar{U}_1 + (1 - \bar{U}_1) \times \left( \frac{X_i(t) + \bar{X}_s + \bar{X}_a(t)}{3} + h \times \frac{X_i(t) + \bar{X}_s + \bar{X}_a(t)}{3} - X_b(t) \right) \tag{37}$$

where $h$ is the controlling parameter used to regulate the planet's distance from the Sun

$$h = \frac{1}{e^{\tau r}} \tag{38}$$

where $r$ is the random number generated randomly, $\tau$ is linearly decreasing from 1 to -2.

$$\tau = (a_2 - 1) \times r_4 + 1 \tag{39}$$

where $a_2$ is the cyclic controlling parameter for T cycle with the optimization process

$$a_2 = -1 \times \frac{t \times \frac{T_{\max}}{T}}{\frac{T_{\max}}{T}} \tag{40}$$

To achieve the best position the following equation is used

$$X_{i,new}(t+1) = \begin{cases} X_i(t+1) & if \quad f(X_i(t+1) \le X_i(t) \\ X_i(t) & else \end{cases} \tag{41}$$

Pseudo code for KOA Algorithm

Start
Set parameters N, $T_{\max}$, $\mu_0$, $\gamma$ and $\bar{T}$
Initialize objects population with position, orbital period, eccentricities using Eq.
Initial population fitness value evaluation
Define the global best solution $(X_s)$
While $t < T_{\max}$
Update $e_i$ for i=1,2,…….N, best (t), worst (t) and $\mu(t)$
for i=1:N
Calculate the Euclidian distance between sun and the object i using
Calculate the gravitational force between sun the object using
Generate two random numbers $r_1$ and $r_2$ between 0 and 1
If $r > r_1$
update the position using Eq.37
else
update the object position using Eq.41
end if
Select the best position of the sun and the object
$t = t + 1$
end for
end while
Stop

## 2.7. Extreme Learning Machine with optimization algorithm

As discussed before, in the ELM classifier the input weights and biases values are randomly generated. Hence, it's necessary to define the number of hidden layers and activation function before the training. To determine the optimal value, the meta heuristic algorithms are used. In this work a new population approach based on meta heuristic optimization algorithm KOA is used with the ELM classifier to determine its parameters. Rashno et al. (2017) proposed a technique to classify mars images with a hybrid feature selection using ant colony optimization (ACO) in the ELM classifier. The selected number of features were finally imported to the ELM classifier to classify mars images. The selected feature with the ELM shows better results when compared to KNN and SVM classifiers. Subudhi & Dash (2021) proposed automatic classification systems for power quality events using the ELM along with the optimization techniques. To extract the feature value S transform is used. Further to optimize the parameters the Grey wolf optimization (GWO) is used.

In this study the Kepler optimization technique is used to optimize the parameters of the ELM classifier. The KOA presents the most favorable search space for exploration and exploitation, since the potential solutions display varying conditions from the Sun at different times. The KOA is a population-based algorithm which selects the candidate solutions at random or by using a custom script. This algorithm provides global exploration and local exploitation rates with good acceptable solutions for complex problems. They are easy to implement and are able to avoid local optima. The procedural steps of the proposed KOA-ELM classifier are shown in Figure 4.

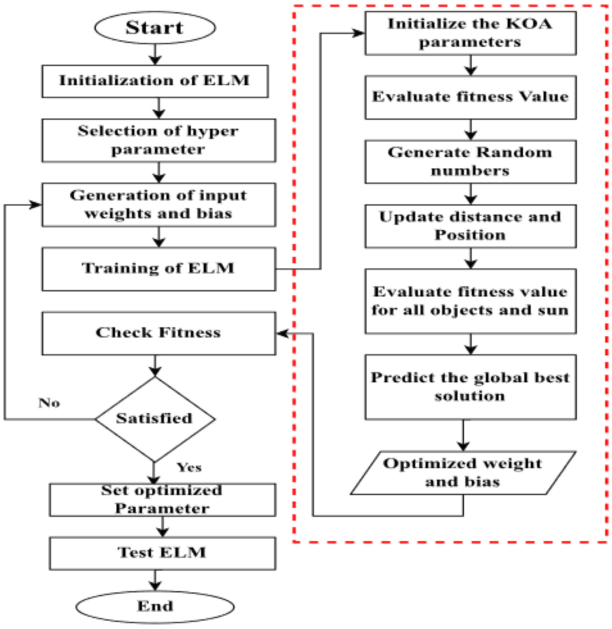


**Figure 4.** Flowchart of ELM- KOA classifier procedural steps

## 3. Experiments and results

To validate the proposed technique efficiency, it is evaluated by using standard datasets like Broatz, KTH-TIPs and F4K fish dataset. The dataset has 93 video samples of 15 different fish species. The life CLEF-15 was created based on the above video samples. The dataset was collected over a period of 5 years of monitoring the Taiwan. To validate the proposed system the following fish species were considered. The training and testing samples split are shown in Table 1.

**Table 1.** Dataset Split-up Details

| Fish Name | Number of Training Sample | Number of Testing Sample |
|---|---|---|
| Abudefduf Vaigiensis | 571 | 171 |
| Acanthurus Nigrofuscus | 3056 | 916 |
| Amphiprion Clarkii | 2876 | 862 |
| Chaetodon Speculum | 125 | 38 |
| Chaetodon Trifascialis | 1419 | 425 |
| Chromis Chrysura | 2712 | 815 |
| Dascyllus Aruanus | 2785 | 835 |
| Hemigymnus Melapterus | 289 | 87 |
| Myripristis Kuntee | 2566 | 769 |
| Neoglyphidodon Nigroris | 180 | 54 |
| Plectrogly-Phidodon Dickii | 2586 | 775 |
| Zebrasoma Scopas | 460 | 138 |

To validate the performance of the proposed classifier, the algorithm is compared with the other existing techniques like Whale Optimization algorithm (WOA) Mirjalili & Lewis (2016), Grey wolf optimization (GWO) Mirjalili et.al. (2014), Chimp Optimization Algorithm (ChOA) Khishe & Mosavi (2020), and Artificial Bee Colony (ABC) algorithm Karaboga & Basturk (2007). Grey wolf optimization (GWO) technique used only one control parameter ranging from 2 to 0. The Particle Swarm Optimization (PSO) technique uses the inertial weight and acceleration constants parameter for tuning the performance. The ABC algorithm uses the colony size of 40 and number of food sources value of 20 for optimizing the parameters. The k-fold cross method was used to validate each classifier model, the value for k being set at 5. For validation different samples are considered for training and testing. Evaluation parameters like accuracy, precision, recall and F-score are used. To better understand the performance the values are plotted in a graph. Obviously, the suggested KOA-ELM technique performs better than the other existing techniques. The proposed technique achieves 99% accuracy on the considered dataset. To validate the proposed algorithm further texture feature datasets are included. The performance of the proposed technique with the existing classifiers is noted in Table 2.

**Table 2.** Performance Comparison of Different Datasets using Various Classifiers

| Dataset Name | Classifiers | Accuracy | Sensitivity | Specificity | Precision |
|---|---|---|---|---|---|
| F4K | SVM | 0.7863 | 0.7441 | 0.7938 | 0.7952 |
| | KNN | 0.8456 | 0.8167 | 0.8210 | 0.8080 |
| | ELM | 0.8564 | 0.8321 | 0.8123 | 0.8124 |
| | ABC-ELM | 0.8632 | 0.8233 | 0.8432 | 0.7695 |
| | WOA-ELM | 0.8842 | 0.8122 | 0.8532 | 0.8546 |
| | Chimp-ELM | 0.8932 | 0.8783 | 0.8623 | 0.8355 |
| | KOA-ELM | 0.9923 | 0.9789 | 0.9898 | 0.9563 |
| Broadz | SVM | 0.8124 | 0.7934 | 0.8111 | 0.8232 |
| | KNN | 0.8245 | 0.8034 | 0.8212 | 0.8432 |
| | ELM | 0.8432 | 0.8425 | 0.8323 | 0.8532 |
| | ABC-ELM | 0.8523 | 0.8232 | 0.8134 | 0.8090 |
| | WOA-ELM | 0.7923 | 0.7623 | 0.7932 | 0.8022 |
| | Chimp-ELM | 0.8212 | 0.8145 | 0.8135 | 0.8412 |
| | KOA-ELM | 0.9523 | 0.8934 | 0.9231 | 0.9323 |
| KTH-TIPS | SVM | 0.8756 | 0.8565 | 0.8464 | 0.8566 |
| | KNN | 0.8699 | 0.8235 | 0.8654 | 0.8658 |
| | ELM | 0.8536 | 0.8255 | 0.8654 | 0.8789 |
| | ABC-ELM | 0.8633 | 0.8456 | 0.8725 | 0.8999 |
| | WOA-ELM | 0.8865 | 0.8789 | 0.8799 | 0.8644 |
| | Chimp-ELM | 0.9456 | 0.9256 | 0.9463 | 0.9563 |
| | KOA-ELM | 0.9846 | 0.9534 | 0.9659 | 0.9789 |

## 4. Conclusion

The present work deals with the classification of fish species. It proposes a new feature descriptor called local energy triangular binary pattern (LETBP) technique to extract features from fish species. This LETBP technique effectively extracts the multi directional information using the angular structure. Three databases, namely Broadatz, KTH-TIPS and F4K are used to validate the efficiency of the proposed technique over the other existing ones. In the feature descriptor LBP, the center pixel is considered as threshold and compared with the neighbourhood pixels. In the proposed scheme, the average value is taken in $3\times3$ matrix and replaced as center pixels to obtain the discriminate feature value. Then, the triangular structure is formed to extract information from all directions. Finally, for the classification, the KOA-ELM hybrid technique is used. The extracted unique feature values are imported to the hybrid model. The proposed method achieves an average classification accuracy of 99.23%, 95.23% and 98.46% for F4K, Brodatz, KTH-TIPS respectively. Moreover, the proposed method is compared with the other existing descriptors like LBP, LDP, LOOP etc. to prove its efficiency.

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