International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Gaussian Golden Search Optimization Based Support Vector Machine Model for Object Detection and Classification in Undersea Water Images

Kaipa Sandhya[1], Jayachandran Arumugam[2]

Submitted: 08/01/2024 **Revised**: 14/02/2024 **Accepted**: 22/02/2024

Abstract: Underwater exploration is critical to the growth and usage of deep-sea assets, underwater autonomy is becoming increasingly vital in order to prevent the hazardous environment of deep sea. Intelligent computer vision is an especially essential component for underwater autonomous operation. Based on the underwater setting, poor light and poor-quality picture augmentation are required as a preprocessing method for aquatic vision. In this study, pre-process the original sea object images with homomorphic filtering to eliminate noise, improve contrast, and adjust the lighting. For segmenting the correct object of an image from the pre-processed image, utilize the level set model. Using the Gaussian Golden Search Optimization-based Support Vector Machine model (G2SO-SVM) technique, identify and categories underwater water images such as fish, corals, rocks, and urchins. MATLAB platform performs implementation and evaluation of the performance of proposed work employing various statistical parameters namely accuracy, specificity, sensitivity, and precision. The proposed work demonstrated higher detection and classification performances than previous state-of-art approaches

Keywords: *Seawater objects detection, Level Set Algorithm, Support Vector Machine and Gaussian Golden Search Optimization.*

1. Introduction

Due to the depletion of natural resources and the growth of the global financial system, interest in researching the undersea environment has increased recently [1]. Additionally, an increasing number of investigations and uses [2] for ocean engineering currently depend on underwater images captured by self-driving submarines. As a result, taking photos underneath using optical imaging [3] gear is more challenging than accomplishing it in the surrounding environment. More specifically, because of potential consequences, noise from lights that are not natural sources, color deformation, and amplification produced on the restricted bandwidth imaging [4] equipment, underwater photos usually deteriorate.

Although the picture's depiction is warped by the external varied frequencies, the scene's magnitude is reduced along with its colors are altered as a result of the eliminated transmitted signal. The underwater [5] item recognition and confirmation that are engaged in underwater region research are impacted by these significant degenerations. In recent years, employing underwater robots to detect and capture microscopic deep-water items has proven to be an efficient way to harvest fish for farming in the sea requiring needing divers. Owing to modern commercial technological advancements, drones [6] may be employed in a variety of settings, such as airborne photography to record landscapes, natural disasters when direct human engagement is impractical, and farmland for replenishing poisons to kill unwanted insects. Amazon is also preparing to use drones to produce goods for customers.

In a word, technological advancements in drone equipment can enhance and increase market potential. The demand for fisheries goods is outpacing the availability of fish and other seafood in many countries due to the cultivation of crops. Moreover, the aquaculture [7] industry is becoming increasingly exposed to substantial losses due to severe warming temperatures. To ensure a profitable crop, it is essential to periodically check on the well-being of marine agricultural organisms like shrimp and clams. A crucial problem that needs to be underlined for marine engineering technology is the growing reliance on the dependability and extreme sensitivity of subsea construction of equipment on several occasions.

Although these methods significantly rely on numerous sensors and can identify underwater objective things to a significant extent, the results are inconsistent, which will affect how effectively each sensor [8] performs in difficult underwater circumstances. As a result, they could satisfy their requirement for accuracy. Seawater's swings, irregular qualities, energy-dispersive pollutants, and illumination suppression, especially in the deep ocean terrain, significantly hamper marine research in comparison to the environment in the atmosphere. As an outcome, using the device's picture and network integration to perform eavesdropping has grown in popularity. Submersible acute vision imaging is a practical method [9] for recognizing

[1]Assistant Professor, School Of Computer Science & Engineering,Presidency University, Bangalore,India
[2]Professor & HOD-CSE,School Of Computer Science & Engineering,Presidency University, Bangalore,India

undersea circumstances.

The exploration of desired accessibility underwater still faces several difficulties, despite the significant advancements in goal acceleration determination on the outermost layer. Object detection [9], a video processing technique, aids in identifying and comprehending the content of videos and pictures. In particular, object detection builds interrelated parts all over these recognized objects, enabling us to determine where each one is about the others in the frame. It allows us to identify and pin down certain elements in a video or image. One of the biggest problems with object recognition is that an item's appearance may change dramatically based on the perspective from which it is seen. Underwater object recognition has particular difficulties, such as low picture quality, difficult-to-detect tiny and numerous targets, and a lack of computational capacity in submarines. The major contribution of this research is pointed as follows:

1. To pre-process the sea object images using homomorphic filtering thereby neglecting noise and getting better contrast as well as correcting illumination.
2. To use a level set model for segmenting the accurate object of an image from the pre-processed image.
3. To detect and classify the undersea water image such as fish corals, rocks and etc by using the G2SO-SVM approach.

Rest of the paper is arranged as; Section 2 recapitulated the literature reviews followed by the proposed work for undersea water object detection is described in Section 3. Section 4 talked about the result part and finally, the paper is completed in section 5.

2. Related Works

Yeh et al. [10] have presented a lightweight deep neural network model to find pictures of items under seawater. The learned image color transition module seeks to convert color photos to comparable color pictures to solve the challenge of submarine color propagation and enhance item detection. Given that underwater photos frequently exhibit color deformation, the recommended color transformation network unit was specifically designed to correct the color aspects of underwater shots for enhanced recognition of objects. The computational complication has reduced efficiency. To identify more photos, underwater items are enlarged.

Peng et al. [11] have described a deep-learning method for automated sea cucumber monitoring using photos from the ocean floor. By offering several hypertext linkages between feature components, the system for recognizing objects Shortcut Property Pyramid Connections improves specific text retrieval and multi-scale structure building while improving the accuracy of specific object recognition, such as sea cucumber. Intensity is increased by using underwater photography. It ought to be examined as well to address the problem of data interpretation.

Kousik et al. [12] have implemented a deep learning model using several neural networks, video significance may be determined. Three separate temporal, local, and locally based indicators are optimized globally. To detect the important items in various diverse video data resources are collected. It is useful and practical in lowering calculation overhead and raising time effectiveness. Therefore, additional data is allowed to facilitate better video sorting.

Chen et al. [13] have modified a node payload balanced ant colony optimal cooperative routing (PB-ACR) protocol. It is important to aggressively change the percentage of knowledge disseminated entities so that correlates with the power supplied by terminals when the environmentally friendly sources of energy of sites are the first constraining factor in the overall sea evaluation. It can raise the provider's throughput and sturdiness while lowering its cost. Network distribution equalization and different data priority for every router thus are yet ignored into consideration.

Zhao et al. [14] suggested a Composited FishNet model for locating and identifying fish in intricate underwater habitats. The supplementary network is connected to the foundation system through a nearby greater-level layout, which removes the influence of complicated primary field data on the component's characteristics. The significant variation in the number of aquatic species is taken into account while designing the loss purpose. The Focalloss coefficient from the multivariate segmentation is used in the coefficient of loss to get the ratio of produced samples with and without positives near 1:3. It is advantageous for enhancing the precision of submerged recognition of objects. Hence, if the structure of the network is additionally optimized to make it cheaper while conserving reliable detection, the method may then be applied in other fields.

Wang et al. [15] highlighted a novel joint iterative network for underwater image enhancement considering the procedure of degrading as an entity and disregarding how color restoration and reducing hazing combine. To manage extreme submarine deformations, a repeated decontamination component is created, which uses the secured recurrent unit as the storage device to slowly optimize the dehazing solutions in several cycles. It enhances image clarity and preserves color. Therefore, real photographs do not have a distribution that is identical to our generated visuals, which causes them to perform poorly in some unique instances.

Qi et al. [16] have demonstrated an underwater target detection network (UTD-Net) creates a unique combined aberrant extractor using traditional techniques to distinguish target-water combined bits, aiming to remove the detrimental impact on the environment. Since it increases the energy of the objects being targeted while rendering them easier to discriminate from the origins, a greater target population would help to increase the precision of identification. However, in real-world applications, intended targets with high targeted sizes recognition continue to be a major obstacle.

Fan et al. [17] have developed mask Regions of Convolutional Neural Networks (RCNN) which guarantee recognition reliability though reducing the system's training variables. It creates a 32-layer system, using 10 leftover pieces in each tier. It can significantly reduce the over-fitting issue brought on by a significant amount of network levels by managing the network elements using a modular framework. It demonstrates the possibilities that deep learning for automatically detecting and segmenting submerged item representations. However, the size of the dataset is inadequate to capture sonar photos.

Pan et al. [18] have evaluated a modified residual neural network (ResNet) method that increases productivity by making reliable identification of items of varied sizes, particularly tiny things, possible through the use of multi-scale processes. It is necessary due to the difficult tasks of submarine administrators, to avoid verification desires and erroneous identifications, and to guarantee the efficient use of maritime assets. This enhancement increases the numerous scale pattern patterns' flexible range and retrieves additional object data. Hence, these findings are from a rather small dataset, hence a bigger dataset is anticipated to substantially improve the suggested methods.

3. Proposed Methodology

Figure 1 outlines the proposed work structure. In the initial stage, an original image pre-processing is held via homomorphic filtering then a level set model is sued to segment the sea objects from an image. At last, this paper proposes a novel Gaussian golden search optimization-based support vector machine model for sea object detection and classification.

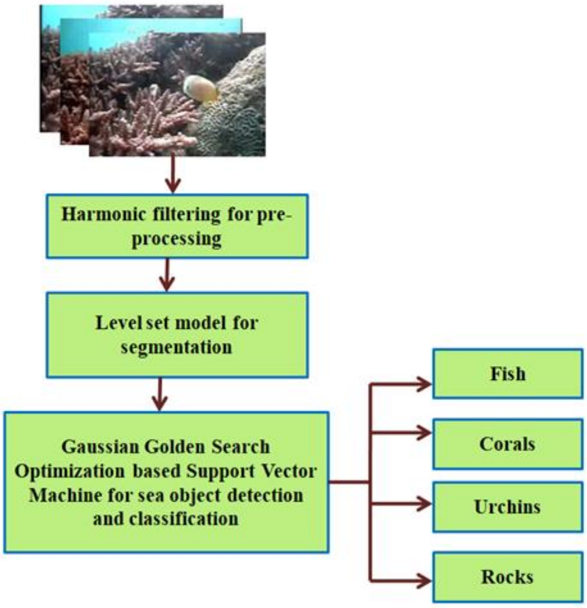

Fig 1: Proposed workflow structure

3.1 Homomorphic filtering for pre-processing

The lack of inconsistency in radiometry, poor visibility and contrast affect the underwater images. An original image is fed for pre-processing. In undersea water object images, the contrast is improved as well as the non-uniform illumination is corrected via homomorphic filtering. Both images sharpen and non-uniform lightings are corrected [19].

$$f(y,z) = IL(y,z) * RE(y,z)$$
(1)

From this, the instrument senses an image $f(y,z)$ with $RE(y,z)$ and $IL(y,z)$ are the reflectance and illumination functions. Here, the low frequencies are suppressed via a high pass filter by multiplying tense components which means it suppressed non-uniformity illumination from the object image. Further, the image quality is enhanced as well the unwanted noises are removed effectively.

3.2 Segmentation using the level set model

Next to pre-processing, the level set model cluster is used for segmentation to cluster the pixels. The closed curve represents a CV with I image on a domain [20].

$$\begin{aligned} &\{CV = \{y \in \delta : \vartheta(y) = 0\} \\ &Exterior(CV) = \{y \in \delta : \vartheta(y) = 0\} \\ &Interior(CV) = \{y \in \delta : \vartheta(y) < 0\} \end{aligned} \quad (2)$$

The curve CV evolves the matching of both exterior to the image background and interior to the region of index (ROI).

Calculate the exterior curve (CV) of an object image then utilizes the step function of smoothed Heaviside.

$$HS_{\ell}(\vartheta) = \begin{cases} 1, & \vartheta > \ell \\ 1, & \vartheta > \ell \\ \frac{1}{2}\left(1 + \frac{\vartheta}{E} + \frac{1}{\pi}\sin\left(\frac{\pi\vartheta}{E}\right)\right), & Otherwise \end{cases}$$

The below equation resolves the evolution of ϑ.

$$\begin{cases} \frac{\partial\vartheta}{\partial t} + f\left|\nabla\vartheta\right| = 0 \\ \vartheta(0, y, z) = \vartheta_0(y, z) \end{cases} \quad (4)$$

Where, $\vartheta_0(y, z)$ is the initial contour and $|\nabla\vartheta|$ is the normal direction. The regulating force f utilizes an edge indication function to stop the evolution level set of the nearest solution or pixel.

$$G = \frac{1}{1 + \left|\nabla\left(g_{\chi} * I\right)\right|^2} \quad (5)$$

Sea object image gradient operation is ∇ in which g_{χ} and I are the Gaussian smoothing kernel and image. The below equation represents the entire level set model to segment the sea object.

$$\frac{\partial\vartheta}{\partial t} = G\left|\nabla\vartheta\right| = \left(div\left(\frac{\nabla\vartheta}{|\nabla\vartheta|} + V\right)\right) \quad (6)$$

The customized force is V and $div\left(\frac{\nabla\vartheta}{|\nabla\vartheta|}\right)$ is the approximate mean curvature.

3.3 Detection and Classification of undersea objects

This section discusses the undersea water object detection and classification by means of Gaussian Golden Search Optimization (G2SO) based Support Vector Machine (SVM). Particularly, the SVM performance during classification is boosted with the usage of the G2SO model.

3.3.1 Gaussian Golden Search Optimization (G2SO) approach

The Golden Search Optimizer (GSO) is a basic meta-heuristic algorithm based on regularly used methods and ideas of meta-heuristic models. The GSO algorithm's basic three components are population initialization, population analysis, and current population updating.

Initializing solution population and evaluation:

The search space is initialized by randomly generated clusters with the GSO search procedure [21]. Consider Equation (7) below

$$LO_j = Lb_j + random \times \left(Ub_j - Lb_j\right); \qquad j = 1, 2, ..., M$$

The j^{th} object position, according to the search space, with Lb_j and Ub_j is the lower and upper limits of GSO. Evaluate the original population and choose the clusters with the highest fitness value based on the goal function.

Golden changing and size evaluation:

Sort the oceanic items according to the fitness value, and the random solution varies the poorest fitness associated with the things. In every iteration, the underwater objects are shifted to the step size operator and best solution. The transform operator (*t*) balances GSO local and global search. Determine the distances between the best and current locations of underwater items. Where, 1 and 0 are random sine values. During the iteration, the following equation is updated and SZ_j produced at random.

Consider Equation (8) below

$$SZ_j(T+1) = t \cdot SZ_j(t) + B_1 \cdot \cos(r_1) \cdot \left(Best_{LO_j} - y_j(t)\right) + B_2 \cdot \sin(r_2) \cdot \left(Best_{LO_j} - y_j(t)\right)$$

Where, B_1 and B_2 have random values of 0 and 2 in which the ranges of random integers r_1 and r_2 are 0 and 1. With a transfer operator, the maximum number of iterations is Max_t, and the equation below evaluates the decreasing function of *T*.

$$T = 100 \times Exp\left(-20 \times \frac{t}{Max_t}\right) \quad (9)$$

Step size limitation enhancement via Gaussian step and update new position:

Wider cycles of clusters are permitted in problem space, and stochastic variables have a step size of (8). Divergence and explosion are avoided based on the clusters in order to manage the oscillations in GSO. As a result, we proposed a Gaussian mutation using GSO to overcome GSO's step size constraints. The Gaussian function prevents local optima trapping, which improves GSO's global search capabilities. The Gaussian density function is defined in the formula below.

$$Guassian_{(0,\delta^2)}(\delta)=\frac{1}{\sqrt{2\pi\sigma^2}}e^{-\delta^2/2\omega^2} \quad (10)$$

Ranges of the random Gaussian function are δ and σ. Move the subsea item to the global optimum of search space in G2SO by expressing the phrase below.

Fuzzy logic based hybrid kernel SVM

Support Vector Machines (SVM) based on statistical learning theory, are introduced by Vapnik (1995). Vapnik constructed the standard SVM to separate training data into two classes. The goal of the SVM is to find the hyperplane that maximizes the mini- mum distance between any data point. SVM has been successfully applied in classification and function estimation problems, but some limitations exist in the SVM theory. Traditionally, we know each sample {xi,yi} in the training dataset belongs to either one class or the other, i.e., the value of yi is only assigned to 1 or -1. All samples in training dataset are treated uniformly in the same class during the learning process of SVM. The hyper plane of SVM and FSVM is shown in Figure 5.

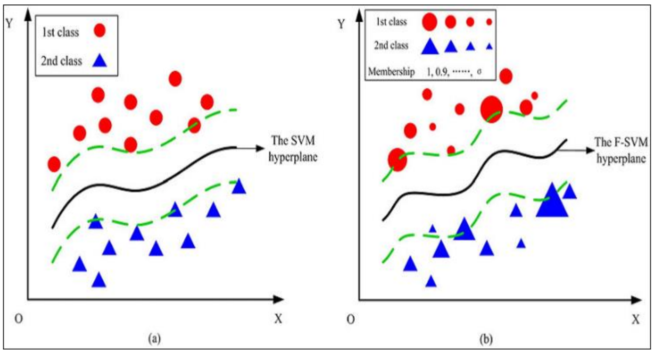

Fig 5: (a) The diagram of the SVM algorithm, (b) the diagram of the F-SVM algorithm

In practical classification problems, the effects of the samples in training dataset may be different. Usually, some of samples in training dataset are corrupted by noise, which is introduced during sampling. These samples are called outliers, and usually less important than others. In fact, that we care about the meaningful samples can be classier correctly. In short, a sample in the training dataset may not completely belong two classes and 10% is meaningless, or we say that the sample belongs to one of two classes with 90% confidence. In other words, each training sample (xi ,yi) is associated with a fuzzy membership (0<=si<=1). This fuzzy membership si indicates the certainty that the sample belongs to one of two classes is si, and the value 1–si can be regarded as meaningless in the classification problem.

In 2002, Lin & Wang (2002) [15] introduced Fuzzy Support Vector Machine (FSVM) by incorporating fuzzy membership into standard SVM. In the FSVM, each sample xi, yi in the training data is weighted by using fuzzy membership function. It becomes as xi, yi, si where Si is the fuzzy membership, i.e., the confidence of this sample belong to one of two classes. Then the optimal hyperplane problem in SVM is reformulated as (Shi *et al.* 2006) , the fuzzy membership function for reducing the effect of outliers is a function of the distance between each data point and its corresponding class center, and the function is represented with parameters of the input space. Here Fuzzy membership function is applied to each input data of SVM, the fuzzy training set is given in Equation (7).

$$\{(x_i, y_i, s), i=1,2,\ldots n; x_i \in R^d; y_i \in \{1,-1\}; \lambda < s_i < 1\}$$

Here λ is a small positive number.

The optimal hyper plane problem of FSVM is defined in Equation (8):

$$\min_{w,\varsigma}\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} f_i\varepsilon_i \quad (8)$$

$$\text{Subject to} \quad \begin{array}{ll} y_i(w.x_i+b) \geq 1-\varepsilon_i & \\ \varepsilon_i \geq 0 & , i=1,\ldots\ldots\ldots n \end{array}$$

Where $f_i(0 \leq f_i \leq 1)$ is the fuzzy membership function, $f_i\varepsilon_i$ is a error of different weights and C is a constant

FSVM follows the structural risk minimization principle from the statistical learning theory. Its kernel is to control the practical risk and classification capacity in order to broaden the margin between the classes and reduce the true costs [12].A Fuzzy support vector machine searches an optimal separating hyper-plane between members and non-members of a given class in a high dimension feature space.

The Lagrange multiplier function of FSVM is given in Equation (9): Consider below Equation (9).

$$L(w,b,\xi,\beta) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} f_i\xi_i - \sum_{i=1}^{n}\alpha_i(y_i(wz_i+b)-1+\xi_i) - \sum_{i=1}^{n}\beta_i$$

Which satisfies the following parameter condition

$$w - \sum_{i=1}^{n}\alpha_i y_i z_i = 0$$

$$-\sum_{i=1}^{n}\alpha_i y_i = 0$$

$$f_i C - \alpha_i - \beta_i = 0$$

Then the optimization problem is transferred, it is defined in Equation (10):

$$Max \quad W(\alpha) = \sum\alpha_i - \frac{1}{2}\sum\alpha_i\alpha_j y_i y_j k(x,y) \quad (10)$$

Subject to $\sum \alpha_i y_i = 0$

$0 \le \alpha_i \le f_i C \;\; , \; i = 1, 2, ..., n$

Where the parameter α_i can be solved by the Sequential Minimal Optimization (SMO) quadratic programming approach

We have analyzed the kernel equation from the existing work
(Chen *et al.* 2012) and used them in the proposed work, namely, RBF and quadratic function.

Radial basis function: The support vector will be the centre of the RBF and σ will determine the area of influence. This support vector has the data space, it is given in Equation (11):

$$K(x_i, x_j) = \exp(-\frac{\left\| x_i - x_j \right\|^2}{2\sigma^2} \qquad (11)$$

Quadratic kernel function: Polynomial kernels are of the form $K(\vec{x}, \vec{z}) = (1 + \vec{x}^T \vec{z})^d$. Where $d = 1$, a linear kernel and $d = 2$, a quadratic kernel are commonly used.

Let $k_1(RBF)\, and\; k_2(Quadratic)$ be kernels over $\Xi \times \Xi,\; \Xi \subseteq R^p$,and k_3 be a kernel over $R^p \times R^p$. Let function $\varphi : \Xi \to R^p$. The two kernels based formulations are represented in Equations (12 and 13):

$$k(x, y) = k_1(x, y) + k_2(x, y) \text{ Is a Kernel} \qquad (12)$$

$$k(x, y) = k_1(x, y) k_2(x, y) \text{ Is a kernel} \qquad (13)$$

Substitute the Equations (12) and (13) in Lagrange multiplier Equation (6) and get the proposed hybrid kernel. It is exposed in
Equation (14):

$$Max \quad W(\alpha) = \sum \alpha_i - \frac{1}{2} \sum \alpha_i \alpha_j y_i y_j (k_1(x_i . x_j) + k_2(x_i x_j))$$

$$Max \quad W(\alpha) = \sum \alpha_i - \frac{1}{2} \sum \alpha_i \alpha_j y_i y_j (k_1(x_i . x_j) k_2(x_i x_j))$$

3.3.2 ***G²SO-based FSVM for undersea object detection and classification:***

SVM is the most popularly used classification model or machine learning model in which large-scale learning is enhanced by focusing on linear SVM. Generally, SVM consists of various advantages for classification such as performing reasonably effectively if there is an obvious difference between categories, greater efficacy in high-dimensional areas and using less memory and when the dimensions exceed the total amount of samples, this method is efficient. Although, it faces a few challenges in terms of overlapping issues, unsuitable for larger dataset classification and the performance will reduce due to the data point based on the number of features being more than the total amount of data points used for training samples [22]. For this reason, the G^2SO algorithm is adopted for augmenting the performance of SVM such as kernel, loss function and regularization. Figure 2 exemplifies the classification of the proposed G^2SO-based SVM.

SVM undergoes training by dividing the data training into hyperplanes that correlate to the segmented seawater objects. It is mainly constituted by vectors of support that frequently comprise vector subsets. For vector detection, used as support vectors, one may improve the SVM's decision-making capabilities. Where, $y \in \Re^m$ and WV are the vector and weighted vectors with two categories such as $z_k \in \Re^l$. The regularization function solves the primal issues.

$$\min_{WV} imum\; WV^T WV + d \sum_{k=1}^{m} \left(\max imum \left(0, 1 - y_k WV^T z_k \right) \right)$$

$$\min_{\chi} imum\; \chi^T \overline{R} \chi^{-e^T} \chi$$

Where, $\overline{R} = R + 1$ and $R_{jk} = y_k y_i z_k^T z_i$ diagonal matrix and vectors and the regularization generates *WV* as a sparse solution.

$$\min_{WV} imum \left| \; WV \right|_1 + d \sum_{k=1}^{m} \left(\max imum \left(0, 1 - y_k WV^T z_k \right) \right)^2$$

Both $| \;\; |_1$ and $d > 0$ are the penalty parameters. G^2SO-based FSVM chooses the cot parameter *d* during SVM training. The value *d* pre-defines the function of cross-validation. The size of the training dataset election is subjected to the dividing sub-set of testing data. The performance of undersea object classification is boosted in which *l* is the number of eater objects for classification that is described as $dm(l)_{G^2SO-SVM}$. Finally, the undersea objects namely fishes, corals, urchins and rocks are effectively classified with the help of G^2SO-based FSVM. The overall flow diagram of the proposed SVM-based G^2SO is illustrated in Figure 2.

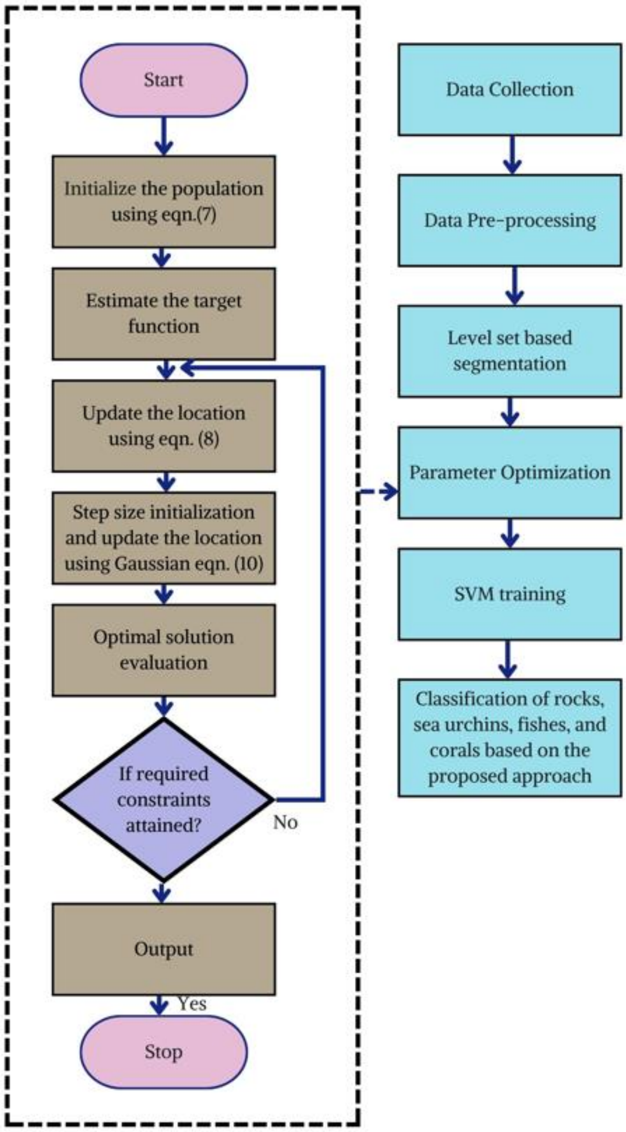

Fig 2: Overall schematic of FSVM- G^2SO

4. Experimental Analysis:

This section demonstrated the performance analysis of the proposed work with its experimental setup and dataset used. The details are elucidated in the following section.

4.1 Experimental setup

For the simulation, we have utilized MATLAB 2008a simulator running in the system with the specification of NVIDIA GeForce GTX 1080 Ti-GPU, 64 GB RAM along with Intel 5 core processor.

4.2 Dataset Description

For the performance analysis we have taken Enhancing Underwater Visual Perception (EUVP) [23] dataset which included paired and unpaired image samples of better and worst quality images to demonstrate the supervised training of image enhancement approaches. There are a total 12568 images and some of the sample images are depicted in Figure 3.

Fig 3: Sample images from the dataset

4.3 Classification Assessment

This section is to present the assessment based on the proposed classification approach and state of artworks such as SVM, Random Forest, and GA-FSVM. The proposed approach effectively classifies the sea urchins, corals, rocks and fishes. The effectiveness of classifying the above-said objects is lesser as shown in figure 4 and 5.

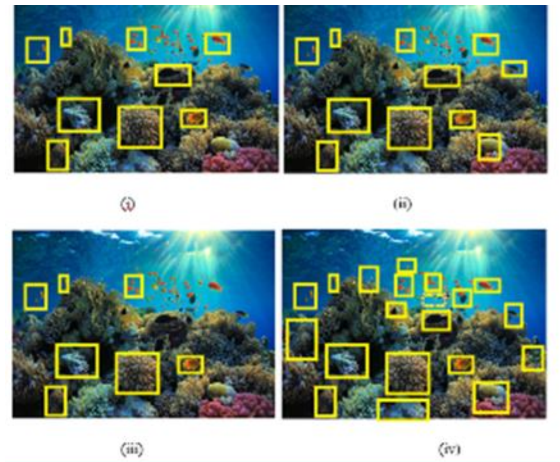

Fig 4: Classified results sample 1 image: (i) SVM, (ii) Random Forest, (iii) GA-FSVM, and (iv) proposed

From Figures 4 and 5, it is evident that the methods SVM, Random Forest and SVM with GA optimization algorithm classify the sea urchins, rocks, fish and corals not in an optimized way. The proposed method utilizes a Gaussian golden search algorithm which precisely tunes the SVM and hence the classification of all those items is accurate as shown in figure (4) (iv) and figure (5) (iv).

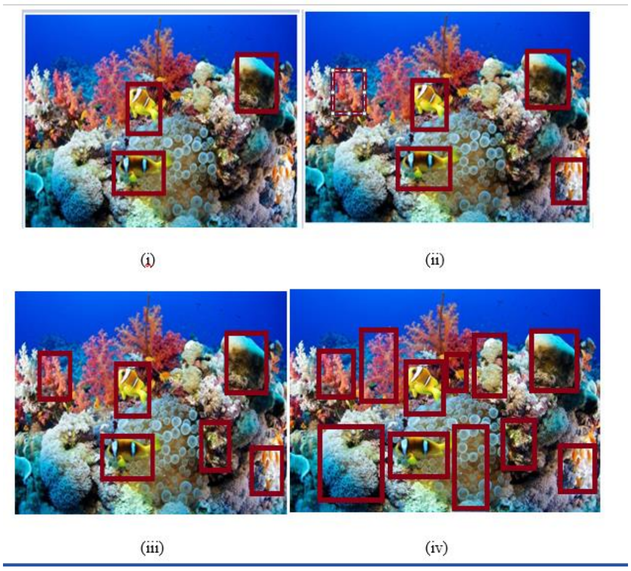

Fig 5: Classification results in sample image 2: (i) SVM, (ii) Random Forest, (iii) GA-FSVM, and (iv) Proposed

The experimental results of the proposed GA-FSVM method using in SUIM dataset [23] dataset are given in Table 2 and the UIEBD dataset [24].is given in Table 3.

Table 2. Comparison of the different classification methods in the SUIM dataset.

Method	IoU	DSC	Acc	Se	Sp	Pr
UNet [27]	94.24	97.21	97.89	97.44	98.31	97.11
ResUNet [30]	93.23	95.28	97.42	96.19	97.67	96.89
DeepLabV3 [29]]	92.53	96.88	97.12	97.29	97.67	96.89
ResUNet++ [28]	93.23	97.88	96.98	96.19	97.67	96.89
DFANet [26]	90.11	94.22	92.34	92.31	92.23	92.21
SegNet [25]	91.61	95.12	91.89	90.12	92.11	92.23
Proposed GA-FSVM	**97.34**	**98.74**	**98.34**	**98.63**	**98.23**	**97.89**

Comparing the proposed method with other modified ResUNet architectures [25-30] in Table 2 shows that the proposed method performs well on the SUIM test dataset. This is because there is a relatively large gap between the quantitative criteria obtained by the architectures designed in [25-30]. However, the segnet [25] and DFANet [26]architectures have better performance than the proposed **GA-FSVM**, as the formers have filters of different sizes that can retrieve spatial information more accurately. On the other hand, as reported in Table 3, the proposed architecture achieves good performance compared to other ResUNet-based architectures due to the use of the transfer learning technique.

Table 3. Comparison of the different **classification** methods in the UIEBD dataset.

Method	IoU	DSC	Acc	Se	Sp	Pr
UNet [27]	92.23	96.38	97.12	96.19	97.67	96.89
ResUNet [30]	90.98	93.98	96.84	96.13	97.17	94.21
DeepLabV3 [29]]	85.99	92.81	97.12	96.89	97.34	89.26
ResUNet++ [28]	90.98	93.98	96.84	96.13	97.17	94.21
DFANet [26]	94.14	97.21	97.89	97.11	98.51	97.11
SegNet [25]	91.61	95.12	91.89	90.12	92.11	92.23
Proposed GA-FSVM	**96.23**	**97.67**	**98.34**	**98.78**	**98.45**	**96.89**

4.4 Performance analysis

For analyzing the performance of the proposed approach we have taken the statistical parameters such as accuracy, specificity, sensitivity, and precision. The performances are compared with state-of-art works such as SVM, RF, and GA-FSVM. Figure 6 illustrates the performance estimation based on the accuracy of the classification of seawater objects such as corals, rocks, fishes, and sea urchins. The proposed approach shows better accuracy of 97.34% and other approaches such as SVM, RF, and GA-FSVM possess accuracy of 85%, 89%, and 93.29% respectively. Thus the proposed approach surpasses all the other approaches.

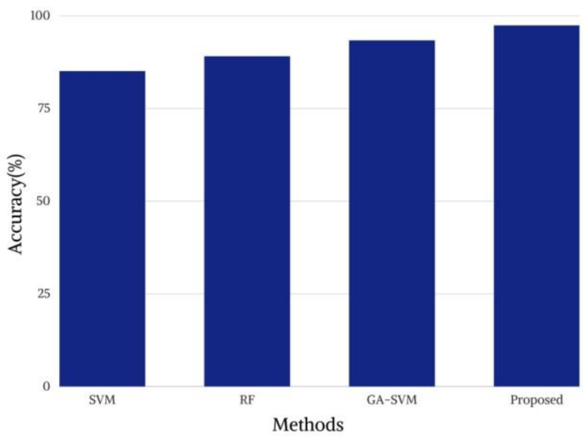

Fig 6: Performance estimation based on the accuracy

The performance analysis based on the specificity is illustrated in Figure 7 and from the figure, it is evident that the proposed approach achieves a specificity of 96.5% and other approaches SVM, RF, and GA-FSVM accomplished lower specificity of 84%, 87%, and 92.56% correspondingly. This is due to the fact that the proposed approach effectively classifies the true positive and true negative values.

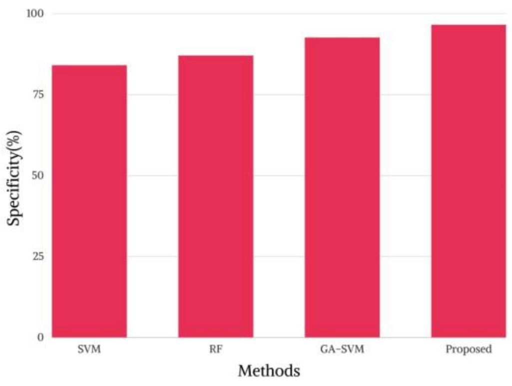

Fig 7: Performance estimation based on Specificity

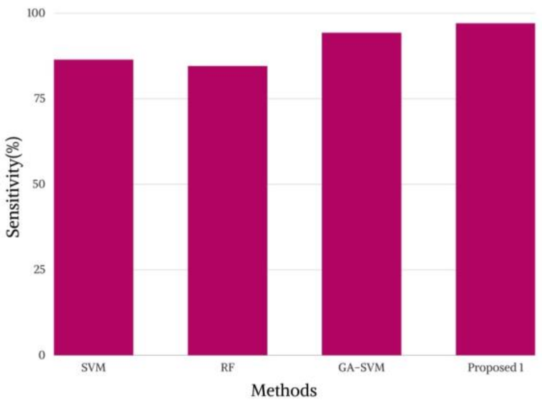

Fig 8: Performance estimation based on Sensitivity

The graphical representation of the sensitivity-based comparative study is shown in Figure 8. The proposed approach achieves higher sensitivity of 97.02% and surpasses all the other approaches such as SVM, RF, and GA-FSVM. Moreover, the graphical representation of the comparative study based on the precision is illustrated in Figure 9. The proposed approach ensures higher precision of 98.34% and other approaches SVM, RF, and GA-FSVM achieve lower precision of 81.40%, 85.67%, and 92.78% respectively.

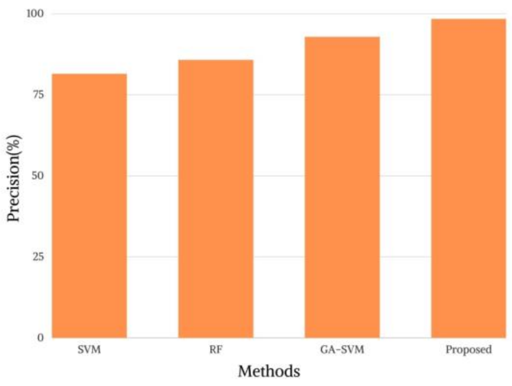

Fig 9: Performance estimation based on precision

5. Conclusion

In a nutshell, the proposed work is based on G^2SO-based SVM for the classification of underwater objects such as fishes, sea urchins, rocks, and corals from the underwater images. The prediction is to find the possibilities of livelihood of sea animals. The proposed approach utilized G^2SO for the tuning of SVM which effectively tuned the SVM to achieve better classification results. The proposed approach is analyzed with MATLAB 2008a simulator and compared the performance with state-of-art works such as SVM, RF, and GA-FSVM and concludes that the proposed work classifies the objects more effectively than the other approaches. Further, the accuracy, specificity, sensitivity, and precision of the proposed approaches are 97.34%, 96.5%, 97.02%, and 98.34% respectively.

References

[1] Amani, M., Mahdavi, S., Kakooei, M., Ghorbanian, A., Brisco, B., DeLancey, E.R., Toure, S. and Reyes, E.L., 2021. Wetland Change Analysis in Alberta, Canada Using Four Decades of Landsat Imagery. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 14, pp.10314-10335.

[2] Abualigah, L., Diabat, A., Sumari, P. and Gandomi, A.H., 2021. Applications, deployments, and integration of internet of drones (iod): a review. IEEE Sensors Journal, 21(22), pp.25532-25546.

[3] Huang, W., Shu, X., Wang, Z., Chen, C., Zhang, Y., Zhang, L. and Xu, J., 2022. Boundary-Aware Network With Topological Consistency Constraint for Optic Chiasm Segmentation. IEEE Transactions on Artificial Intelligence.

[4] Bian, X., Li, G., Wang, C., Liu, W., Lin, X., Chen, Z., Cheung, M. and Luo, X., 2021. A deep learning model for detection and tracking in high-throughput images of organoid. Computers in Biology and Medicine, 134, p.104490.

[5] Wei, X., Guo, H., Wang, X., Wang, X. and Qiu, M., 2021. Reliable data collection techniques in underwater wireless sensor networks: A survey. IEEE Communications Surveys & Tutorials, 24(1), pp.404-431.

[6] Zhu, P., Wen, L., Du, D., Bian, X., Fan, H., Hu, Q. and Ling, H., 2021. Detection and tracking meet drones challenge. IEEE Transactions on Pattern Analysis and Machine Intelligence, 44(11), pp.7380-7399.

[7] Amundsen, H.B., Caharija, W. and Pettersen, K.Y., 2021. Autonomous ROV inspections of aquaculture net pens using DVL. IEEE Journal of Oceanic Engineering, 47(1), pp.1-19.

[8] Ramanujam, E., Perumal, T. and Padmavathi, S., 2021. Human activity recognition with smartphone and wearable sensors using deep learning techniques: A review. IEEE Sensors Journal, 21(12), pp.13029-13040.

[9] Kharazi, B.A. and Behzadan, A.H., 2021. Flood depth mapping in street photos with image processing and deep neural networks. Computers, Environment and Urban Systems, 88, p.101628.

[10] Yeh, C.H., Lin, C.H., Kang, L.W., Huang, C.H., Lin, M.H., Chang, C.Y. and Wang, C.C., 2021. Lightweight deep neural network for joint learning of underwater object detection and color conversion. IEEE Transactions on Neural Networks and Learning Systems.

[11] Peng, F., Miao, Z., Li, F. and Li, Z., 2021. S-FPN: A shortcut feature pyramid network for sea cucumber detection in underwater images. Expert Systems with Applications, 182, p.115306.

[12] Kousik, N., Natarajan, Y., Raja, R.A., Kallam, S., Patan, R. and Gandomi, A.H., 2021. Improved salient object detection using hybrid Convolution Recurrent Neural Network. Expert Systems with Applications, 166, p.114064.

[13] Chen, Y., Tang, Y., Fang, X., Wan, L., Tao, Y. and Xu, X., 2021. PB-ACR: Node payload balanced ant colony optimal cooperative routing for multi-hop underwater acoustic sensor networks. IEEE Access, 9, pp.57165-57178.

[14] Zhao, Z., Liu, Y., Sun, X., Liu, J., Yang, X. and Zhou, C., 2021. Composited FishNet: Fish detection and species recognition from low-quality underwater videos. IEEE Transactions on Image Processing, 30, pp.4719-4734.

[15] Wang, K., Shen, L., Lin, Y., Li, M. and Zhao, Q., 2021. Joint iterative color correction and dehazing for underwater image enhancement. IEEE Robotics and Automation Letters, 6(3), pp.5121-5128.

[16] Qi, J., Gong, Z., Xue, W., Liu, X., Yao, A. and Zhong, P., 2021. An unmixing-based network for underwater target detection from hyperspectral imagery. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 14, pp.5470-5487.

[17] Jayachandran, A & Dhanasekaran, R, “Severity Analysis of Brain Tumor in MRI Images using Modified Multi-Texton Structure Descriptor and Kernel- SVM, The Arabian Journal of science and engineering October 2014, Volume 39, Issue 10, pp 7073-7086,(2014).

[18] Pan, T.S., Huang, H.C., Lee, J.C. and Chen, C.H., 2021. Multi-scale ResNet for real-time underwater object detection. Signal, Image and Video Processing, 15, pp.941-949.

[19] Sherine, A.N.L.I. and Peter, G., 2021. A novel biometric recognition system for fingerprint using polar harmonic transform. International Journal of Pharmaceutical Research, 13(01).

[20] Jayachandran, A and R.Dhanasekaran ,(2017) ‘Multi Class Brain Tumor Classification of MRI Images using Hybrid Structure Descriptor and Fuzzy Logic Based RBF Kernel SVM’ , Iranian Journal of Fuzzy system , Volume 14, Issue 3, pp 41-54 , 2017.

[21] Mahiba C, A Jayachandran,"Severity analysis of diabetic retinopathy in retinal images using hybrid structure descriptor and modified CNNs",Measurement,Vol 135,PP 762-767,2019.

[22] Jayachandran, A, ‘Abnormality segmentation and Classification of multi model brain tumor in MR images using Fuzzy based hybrid kernel SVM’ International Journal of Fuzzy system , published by Springer, Volume 17, Issue 3, pp 434-443,2018.

[23] Islam, M. J., Edge, C., Xiao, Y., Luo, P., Mehtaz, M., Morse, C., Enan, S. S., & Sattar, J. (2020).Semantic Segmentation of Underwater Imagery: Dataset and Benchmark. IEEE International Conference on Intelligent Robots and Systems, 1769–1776. DOI: https://doi.org/https://doi.org/10.1109/IROS45743.2020.9340821

[24] .Li C., Guo C., Ren W., Cong R., Hou J., Kwong S., et al. An underwater image enhancement benchmark dataset and beyond. IEEE Trans. Image Process. 2019, 29, 4376–4389.

[25] Badrinarayanan V.; Alex K.; Roberto C. Segnet: A deep convolutional encoder-decoder architecture for image segmentation. IEEE Trans. Pattern Analy. Mach. Intel. 2017, 39, 2481–2495.

[26] Li H.; Xiong P.; Fan H.; Sun J. Dfanet: Deep feature aggregation for real-time semantic segmentation.In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, (2019).

[27] Ronneberger, O., Fischer, P., Brox, T.: U-net: Convolutional networks for biomedical image segmentation. In: International Conference on Medical Image Computing and Computer-assisted Intervention, pp. 234–241

[28] Yang Z, X. Peng, and Z. Yin, “Deeplab v3 plus-net for image semantic segmentation with channel compression,” in Proceedings of IEEE 20th International Conference on Communication Technology (ICCT). IEEE, 2020, pp. 1320–1324.

[29] Li H.; Xiong P.; Fan H.; Sun J. Dfanet: Deep feature aggregation for real-time semantic segmentation.In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, (2019).

[30] Jha D, Smedsrud PH, Riegler MA, Johansen D, De Lange T, Halvorsen P, et al., editors. Resunet++: An advanced architecture for medical image segmentation. 2019 IEEE International Symposium on Multimedia (ISM); 2019: IEEE.