Turkish Journal of Computer and Mathematics Education Vol.12 No. 11 (2021), 6269 - 62479
Research Article

Modified Grey Wolf Optimization Algorithm (mGWO) For Detection and Diagnosis of Pancreatic Tumor Using Region Based Segmentation Techniques

S. Arulmozhi[1], Dr.R. Shankar[2] and Dr. S. Duraisamy[3]
[1]Research Scholar, PG & Research Department of Computer Science, Chikkanna Government Arts College, Tirupur-641 602
[2&3]Assistant Professors, PG & Research Department of Computer Science, Chikkanna Government Arts College, Tirupur-641 602.

Article History: Received: 11 January 2021; Revised: 12 February 2021; Accepted: 27 March 2021; Published online: 10 May2021

Abstract: Pancreatic cancers are strange progression of cell in intestinal enzymes and hormone generating cell. Pancreatic adenocarcinoma is perhaps the most severe threatening tumors which stay the fourth driving reason for the disease related demise. The anticipation for patients determined to have this pancreatic tumor has consistently remained remarkably poor. Unlike brain, pancreas is not secured by skull. It is bounded by numerous organs and greasy tissues in the stomach and hence recognition and dissection is highly inappropriate. Still, pancreatic cancer can be healed if it is noticed at a primary phase. But, most of the abdominal CT images contain noises in addition to the visceral fat in the proximity of pancreas makes it very challenging for timely detection. Various methodologies like Duck Traveller Optimization (DTO), Improved Duck Traveller Optimization (IDTO) and Grey Wolf Optimization (GWO) is utilized in this pancreatic cancer detection. The results are not much accurate by considering the above said methods. In this paper, an effort is made to identify pancreatic tumor using modified Grey Wolf Optimization (mGWO). Proper image processing procedures and a classifier is utilized to identify the tumor. After the pre-processing stage, smallest distance classifier is adopted towards noticing the tumorous part in the image. It is witnessed that the accurateness of discovering tumor is about97% in the proposed mGWO.

Key words: Pancreatic Cancer, Duck Traveller Optimization, Grey Wolf Optimization.

Introduction

In general, energetic cells nurture in a usual and meticulous manner contrasting the diseased cells. Pancreatic cancer is developed from cells that propagate without any control and gradually developing a lump in pancreas. Early determination of this tumor is demanding. Despite the fact that it gets recognized, it is important to take extraordinary consideration not permitting it to spread further as it might get hopeless where medical procedures may also become helpless. Pancreatic cancers are separated into two groups, specifically exocrine and endocrine tumor; the way it behaves and its treatment procedures are entirely dissimilar. Over 95% of the tumor are recorded to exocrine while under 5% of all pancreatic tumors record to endocrine tumors. Pancreatic adenocarcinoma [14] is a low incident but extremely mortal syndrome. By 2030 it is anticipated to be the second prominent reason of all cancer demises. While there is no curious explanation actually found, on why an individual is influenced by tumor. A portion of the components prompting this sickness are smoking, diabetes, stoutness, pancreatitis, hereditary misperception and so forth. Research facility results which show high measure of carbohydrate antigen (CA) affirms the presence of tumor [7]

Therapy of this tumor depends on the four phases of cancer prevailing.[10] Stage 1 is the early, restricted and resectable pancreatic disease. Next stage is the place where the tumor begins developing into the duodenum, bile, and the close by tissues of the pancreas is as yet resectable. Stage 3 is privately progressive and incidentally resectable. Stage 4 is much advanced and unresectable. Moderately it is the effect of TNM (Tumor Node Metastasis) [12]. Latest revealing techniques incorporate ANN[11] based image classifier created in MATLAB programming to identify tumors from the PET scan images of affected people. PET is a sort of atomic medication imaging which catches those cells devouring more measure of FDG (Flu-deoxy-glucose).

Related Work

Recently, intelligent optimization [1] for image segmentation strategies considers Otsu's technique, between-class difference, Tsallis entropy, and Kapur's entropy for objective functions. These techniques enhanced the edge through enhancement calculation and got improved outcomes on image segmentation [4]. Additionally, it is evident to analyse ABC with PSO through utilizing between-class fluctuation and Kapur's entropy as target capacities. Kapur's entropy-based ABC exhibited superior execution once there is increase in number of thresholds and lessened time complexity. [5] carried out relative investigation among Kapur's, Otsu, and Tsallis capacities. Outcomes indicate that, in segmentation of images, Kapur's entropy-based calculation achieves improved outcomes compared to the other strategies. In [5], authors have examined the outcomes of

PSO, DPSO and FODPSO. When a comparison of all these are made with Bacteria Foraging (BF)[3] calculation &GA, PODPSO[6] illustrates superior execution in beating optimization and execution issues.

Electromagnetism has been presented for MT by[8], that contrasted it with Kapur's entropy and Otsu's strategy, separately. The trial outcomes confirm that Kapur's entropy is additionally proficient. Prior to that, they checked a similar assessment trial over Harmony Search Optimization & acquired comparative outcomes [2]. Previously, Discrete Gray Wolf Optimizer (GWO) is considered to be primary tool, by fuzzy hypothesis and fuzzy rationale towards accomplishing image dissection. Contrasted to EMO & DE, GWO demonstrates superior execution in segmentation quality and steadiness.

Wolf Pack Algorithm (WPA) [7] is another swarm intelligent technique. As indicated by the wolf pack behaviors, the scientists abstracted 3 insightful practices, searching, calling, and encircling, and two smart principles, the champ bring home all the glory age law of chief wolf [15] and stronger-survive recharging law of wolf pack. The trials indicate that WPA has enhanced convergence and robustness, particularly aimed at huge volume of data.

Wolf Colony Search Algorithm [9] dependent on Leader approach and it is termed as LWCA. The thought of the calculation began since the wonder that there exist separate rivalries between the wolf pack. The sturdiest wolf was chosen as the head of the wolves; the wolves chased prey under the authority of the pioneer, with the goal that they might be highly successful in catching target. The test reveals that the calculation has improved execution on convergence speed and exactness, and it is hard to trap-in local minima.

Incidentally, Grey Wolf Optimizer (GWO) [9]is proposed to get more accurate results in tumor identification. In GWO calculation, α-wolf is likewise claimed as prevailing wolf, the degree of other three sorts diminish, here by 'm' denotes lowermost level wolf. Furthermore, the three principle stages of chasing, looking for prey, surrounding prey, and assaulting prey, are executed.

Improved Grey Wolf Optimizer strategy (IGWO) is another variant of GWO. The technique on boundary choice of IGWO increases the search ability and the hybridization system builds the variety of the agent. Consolidate GWO is proposed with transformation procedure for elucidating the universal optimization issue. By acquainting MDGWO [13] with MT, addresses the issue of thresholds alternative by considering Kapur's entropy for target work. The projected calculation produces superior segmentation outcome, extraordinary effectiveness and precision, and security of the scope of edge.

Existing System

In existing system three algorithms are considered to be important in pancreatic tumor detection. They are Duck Traveller Optimization (DTO), Improved Duck Traveller Optimization (IDTO) and Grey Wolf Optimization (GWO)

Duck Traveller Optimization (DTO)

DTO is used to subdivide the tumor to help the doctors to disease diagnosis.

Pseudo Code of Duck Traveller Optimization (DTO)

Stage 1: Initialization
Stage 2: Assessment
Stage 3: Updation
Stage 4: Subsequent Generation
Initialize Duck Group
While iteration<max_iteration
Produce and categorize ducks
Adjust the locus of ducks and
Categorizing the ducks
Form Duck crowds (D_c)
Spread Ducks in a Row
Then
Assess suitability of duck
group For n=1 to quantity of
ducks Discoveravaricious
ducks
Accomplish the wanderingprocedure
For d=1 to quantity of dimension of ducks Form chick crowds (C_c)

Apprise Duck
individuals Subsequent d
Subsequent n
Update the supreme fitness value

Subsequent Generation
Using this DTO approach can lead to accuracy of 92%.

Improved Duck Traveller Optimization (IDTO)
To review the interpretations from ducks' searchingbehaviour, the subsequenterrands are presented.

Mission 1: Several groups of ducks are together terms as duck populace. Food search movement is being optimized by the ducks of each group.
Mission 2: Height is a fundamental parameter (neck+head) that helps to determine the hunting spot
Mission 3: Ducks usually move as a group and it goes behind their local guide.
Mission 4: After a quantity of jobs, ducks arrive to the place to share with its local affiliates, through communication of exploitation, the places and plenty of food foundations.
Mission 5: In case, the food provision is a smaller amount for the ducks of a certainset to survive, it will move from that location
Mission 6: Based on the satisfaction of end criteria, output the optimal solution. Otherwise, go to Task 2.Its pseudo code is given as below
Stage 1: Populace Initialization
Stage 2: Growth and Reproduction
Stage 3: Competitive exclusion
Stage 4: Robustness calculation
Stage 5: Finding optimal solution
If $i_{max}>i_{final}$
Set $D_{gr}= D_{t1}= D_{t2}= \Phi$;
Initialize $D_tP_{ij}=1/n_i$;
Random();
robustness();
greatest();
recompense();
reprimand ();
Set D_{gr}= Pick_greatest();
Do {
D_{t1}= Pick_ random();
D_{t2}= Pick_ random();
If robustness (D_{t1}) ≥ robustness (D_{t2})
{
recompense(D_{t1});
reprimand(D_{t2});
$D_{gr}= D_{t1}$;
}
Else
{
recompense(D_{t2});
reprimand(D_{t1});
$D_{gr}= D_{t2}$;
}
}while end condition is satisfied;
Return D_g;
D_{gr}denotes greatest duck;
D_{t1} and D_{t2} are two transitory ducks in duck group.
i.e D=(D_{t1}, D_{t1},…. D_{tn}). D_tP_{ij}
i.e P_i=(P_1, P_2,…. P_n) means the probability of food foraging speed (f_{ij}) i.e (j=1,2,…..,n_i).
robustness () is a function to calculate the fitness value of the ducks.

recompense() and reprimand() are two functions used to realize the competitive mechanism.
Where n &n_i = number of ducks in the duck group;
P_i= the survival rate of the i^{th} duck.

Grey Wolf Optimization

Grey Wolf Optimizer (GWO) is a regular swarm-intelligence procedure motivated from the administration chain of command and chasing component of grey wolves. Grey wolves are termed as summit hunters; they require normal gathering size of 5–12. In the progressive system of GWO, alpha (α)- ruling part among the gathering. The remainder of the dependents to α are beta (þ) and delta (ð) - controls most of wolves that are taken as omega (m). The m wolves are of most reduced positioning in the pecking order The numerical arrangement of chasing system of grey wolves comprises the steps mentioned below:

(i) Trailing, hunting, and impending the prey.
(ii) Pursuing, encircling, and bothering the prey till it halts its movement.
(iii) Threatening the prey.

This chasing system can yield an outcome of 95%. To improve this accuracy value, Modified Grey Wolf Optimization is proposed.

Proposed System

Image segmentation includes the procedure & practice of sectioning an image into few specific distinctive parts and mining beneficial contents. Features are extracted using Particle Swarm Optimization (PSO) and Classification is done using Convolutional Neural Network (CNN).

Modified Grey Wolf Optimization (mGWO)

Discovering the global minimum is a regular, testing task among entire minimization strategies. In populace-based optimization techniques, the alluring method to merge in the direction of the global minimum would be separated into 2 essential stages. In the beginning phases of the enhancement, the individuals should be stimulated to disseminate during the whole search space. That is, attempt to investigate the entire search space in its place of grouping nearby local minima. In the final stages, the individuals' needs to exploit data accumulated to unite on the global minimum.

In GWO, with changing boundaries b and B, it is possible to adjust these two stages to discover global least with quick convergence speed. Though various enhancements of individual-based calculations advance local optima evasion, the writing denotes that populace-based calculations are healthier in taking care of this dispute. Despite the contrasts among populace-based calculations, the basic methodology is the detachment of optimization procedure to dual clashing achievements: investigation versus misuse. The investigation urges candidate solutions aimed to adjust suddenly &stochastically. This system increases the variety of the arrangements and reason extra ordinary investigation of the hunt space.

Figure 1 shows the proposed framework

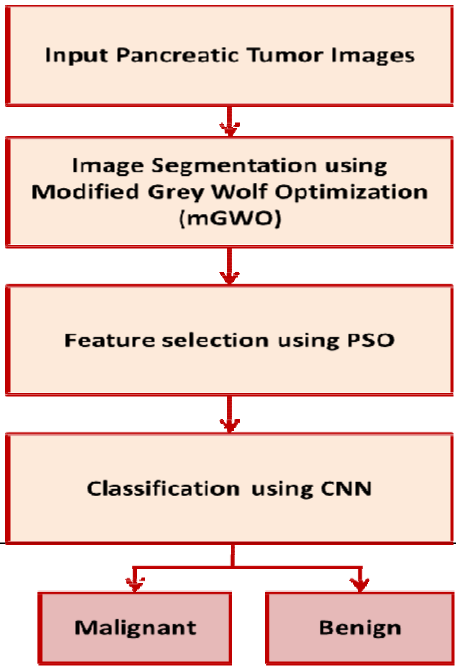


Figure 1: Proposed Framework.

Conversely, the exploitation targets on refining the excellence of solutions via looking locally around the acquired hopeful arrangements in the investigation. In this achievement, candidate solutions are indebted to vary less abruptly and examine locally. A correct harmony between these two achievements can ensure a precise estimation of the global optimum utilizing populace-based calculations. From one viewpoint, simple investigation of the search space stops an algorithm from tracking down an exact estimate of the global optimum.

Set the search agent (grey wolf) populace
$S_l(l = 1, 2, \ldots, n)$
Setb,B and C
Compute fitnessvalues ofevery search agent
S_α= finest search agent
$S_þ$= subsequentto S_α
$S_ð$= subsequent to $S_þ$
while (t<Extreme quantity of repetitions)
for every search agent
refine the point of present search agent
end for
changeb
UpdateB&C
Compute fitness value of all search agents
Refine S_α, $S_þ$,$S_ð$
t++
end while
Return S_α

Features Extraction using Particle Swarm Optimization (PSO)

PSO is a stochastic streamlining method that is like the conduct of a herd of birds or the sociological conduct of a gathering of individuals. Consider a situation wherein a herd of birds are looking for a piece of food around there. Every one of the birds don't actually have a clue where the food is, yet with every cycle they come to realize how far the food is. The best procedure will be to track the bird which is close to food and furthermore since its own past best position. This is the essential thought on which PSO works.

Classification using Convolutional Neural Network (CNN)

CNN is the present prominent design for the task of image categorization. 2-D Convolutional Neural Network (CNN) model is planned utilizing MatConvNet backend for the notable CIFAR10 image recognition task. The entire work process can be to setting up the model, building and assembling the model, preparing and assessing the model and saving the same for reusability. Setting up the data is the initial step of this methodology. Before constructing a network, it is important to set up training and testing content, consolidate data and reshape into the appropriate size. Dataset of standardized information and diversity data can be stored appropriately. Building and incorporating the model is the subsequent phase. To make the CNN, it is mandatory to introduce MatConvNets

Results and Discussion

The National Institutes of Health Clinical Center have done 82 abdominal contrast improved 3D CT scans for 53 males and 27 females. 65 patients with neither main abdominal pathologies nor pancreatic cancer lesions were chosen. Their ages were in the range 18 to 76 years. The CT scans were of resolution 512 x 512 pixels with diverse pixel sizes and slice thickness in the range 1.5 − 2.5 mm.

The Pancreatic Tumor databank is a source of experimentally proven molecular variations related by means of pancreatic cancer in cancer tissues or cancer cell lines. It presently encompasses data related to fluctuations at the mRNA, protein and miRNA stages. The data can be enquired or glanced at mRNA, protein or miRNA levels or grounded on definite cancer subtypes. The results are evaluated based on parameters such as Accuracy, JSC, DSC and time period. Table 1 denotes the outcomes of existing and proposed methodologies

Table 1: Experimental Results

PARAMETER	DTO	IDTO	GWO	MGWO
DSC	0.65	0.72	0.75	0.82
JSC	0.68	0.73	0.77	0.84
time period	3.5	2.8	2.5	2.1
Accuracy	92	94	95	97

Figures 2-5 show the Accuracy, DSC, JSC and Time Period of DOS, IDOS, GWO and MGWO. It is seen that MGWO offers 6%, 4% and 3% better Accuracy in contrast to DOS, IDOS and GWO respectively (Figure 2).It is seen that MGWO offers 27%, 14% and 10% better DSC in contrast to DOS, IDOS and GWO respectively (Figure 3).

It is seen that MGWO offers 24%, 16% and 10% better JSC in contrast to DOS, IDOS and GWO respectively (Figure 4).

It is seen that MGWO involves 67%, 34% and 20% lesser Time Period in contrast to DOS, IDOS and GWO respectively (Figure 5).

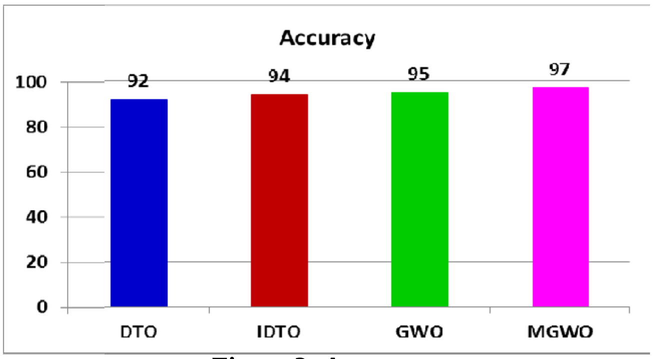


Figure 2: Accuracy.

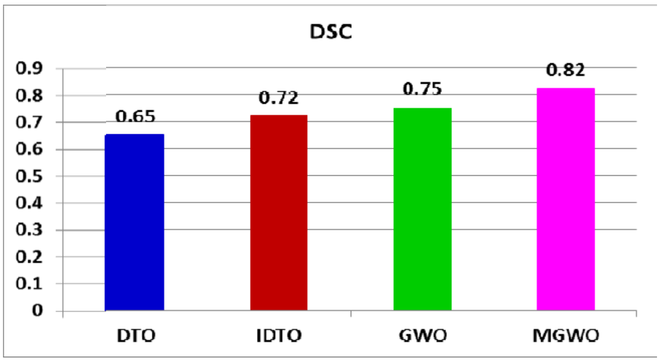


Figure 3: DSC

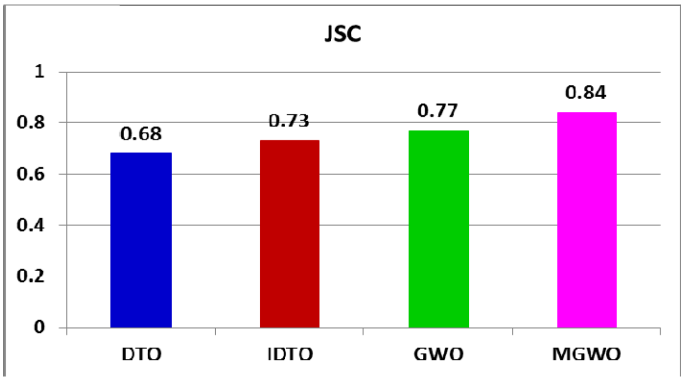


Figure 4: JSC

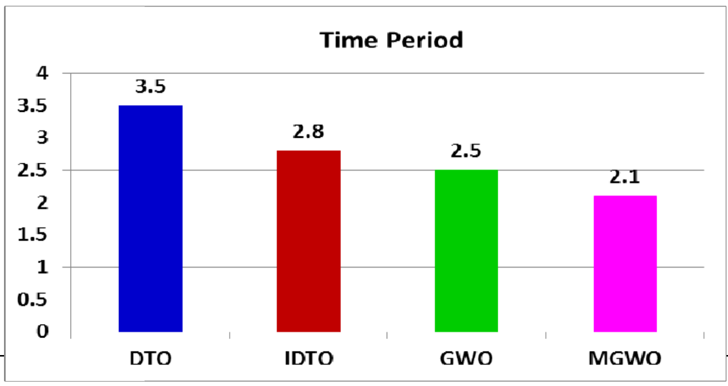
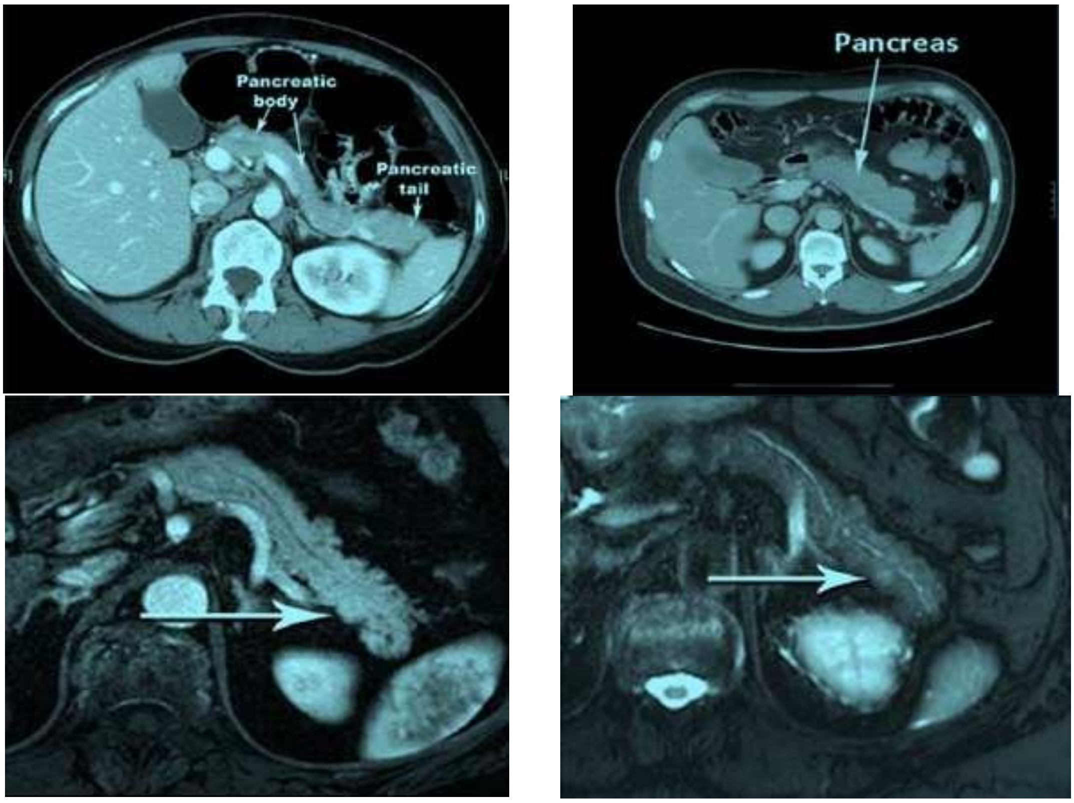


Figure 5: Time Period.

(a) Image-1 CT Scan **(b) Image-1 CT Scan**



(c) Image-3 MRI Scan **(d) Image-4 MRI Scan**

Figure 6: Images of Pancreatic Tumor.

Figure 7: Slice-by-slice Pancreas Segmentation.

Figure 8(a): Image Dataset 1 with Clear Segmentation.

Figure 8(b): Image Dataset 2 with Clear Segmentation.

Figure 8(c): Image Dataset 3 with Clear Segmentation.

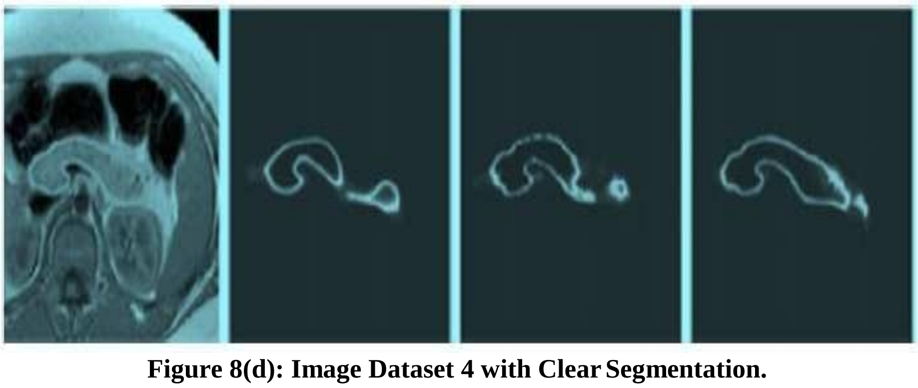


Figure 8(d): Image Dataset 4 with Clear Segmentation.

Conclusions

A variation of Gray Wolf Optimizer is proposed and it is named as mGWO, propelled by the chasing conduct of grey wolves. An exponential decay value is utilized to adjust the investigation and exploitation in the hunt space throughout emphases. The outcomes demonstrated that proposed calculation profits by high investigation in contrast with the standard GWO. The outcomes show that the proposed technique is discovered to be extremely viable for genuine applications because of quick convergence and a smaller amount of opportunities to get trap by the side of local minima. It tends to be presumed that the recommended calculation can beat the current notable and incredible algorithms that exist in the literature work. The outcomes demonstrate the fitness and prevalence of mGWO over current metaheuristic calculations and it has a capacity to turn into a powerful tool for tackling real world issues.

References

1. Akay, B. (2013). A study on particle swarm optimization and artificial bee colony algorithms for

multilevel thresholding. Applied Soft Computing, 13(6), 3066-3091.
2. Arumugam, K., Ramasamy, S., & Subramani, D. Improved Duck and Traveler Optimization (IDTO) Algorithm: A Two-way efficient approach for breast tumor segmentation using multilevel thresholding. European Journal of Molecular & Clinical Medicine, 7(10), 2020.
3. Askarzadeh, A. (2016). A novel metaheuristic method for solving constrained engineering optimization problems: crow search algorithm. Computers & Structures, 169, 1-12.
4. Bhandari, A. K., Kumar, A., & Singh, G. K. (2015). Modified artificial bee colony based computationally efficient multilevel thresholding for satellite image segmentation using Kapur’s, Otsu and Tsallis functions. Expert Systems with Applications, 42(3), 1573-1601
5. Ghamisi, P., Couceiro, M. S., Martins, F. M., &Benediktsson, J. A. (2013). Multilevel image segmentation based on fractional-order Darwinian particle swarm optimization. IEEE Transactions on Geoscience and Remote sensing, 52(5), 2382-2394.
6. Horng, M. H. (2011). Multilevel thresholding selection based on the artificial bee colony algorithm for image segmentation. Expert Systems with Applications, 38(11), 13785-13791.
7. Komaki, G. M., &Kayvanfar, V. (2015). Grey Wolf Optimizer algorithm for the two-stage assembly flow shop scheduling problem with release time. Journal of Computational Science, 8, 109-120.
8. Krishnavenia, A., Shankarb, R., &Duraisamy, S. (2020). An Efficient Methodology for Breast Tumor Segmentation using Duck Traveler Optimization Algorithm. PalArch's Journal of Archaeology of Egypt/Egyptology, 17(9), 7747-7759
9. Li, L., Sun, L., Kang, W., Guo, J., Han, C., & Li, S. (2016). Fuzzy multilevel image thresholding based on modified discrete grey wolf optimizer and local information aggregation. IEEE Access, 4, 6438-6450.
10. Mirjalili, S., Mirjalili, S. M., &Hatamlou, A. (2016). Multi-verse optimizer: a nature-inspired algorithm for global optimization. Neural Computing and Applications, 27(2), 495-513.
11. NajiAlwerfali, H. S., Al-Qaness, M. A., Abd Elaziz, M., Ewees, A. A., Oliva, D., & Lu, S. (2020). Multi-level image thresholding based on modified spherical search optimizer and fuzzy entropy. Entropy, 22(3), 328
12. Oliva, D., Cuevas, E., Pajares, G., Zaldivar, D., & Osuna, V. (2014). A multilevel thresholding algorithm using electromagnetism optimization. Neurocomputing, 139, 357-381.
13. Ren, T., Wang, H., Feng, H., Xu, C., Liu, G., & Ding, P. (2019). Study on the improved fuzzy clustering algorithm and its application in brain image segmentation. Applied Soft Computing, 81, 105503.
14. Resma, K. B., & Nair, M. S. (2018). Multilevel thresholding for image segmentation using Krill Herd Optimization algorithm. Journal of King Saud University-Computer and Information Sciences.
15. Shamsaldin, A. S., Rashid, T. A., Al-Rashid Agha, R. A., Al-Salihi, N. K., &Mohammadi, M. (2019). Donkey and smuggler optimization algorithm: A collaborative working approach to path finding. Journal of Computational Design and Engineering, 6(4), 562-583.