



Research Paper

Multi-Objective Dhole Optimization for Saturation-Aware Autonomous Underwater Forensic Search and Evidence Recovery Missions

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Citation Rajeswari MS, Narayanan P, Balakrishnan A, Manikandan R, Shankar M, Mahadevan N. Multi-Objective Dhole Optimization for Saturation-Aware Autonomous Underwater Forensic Search and Evidence Recovery Missions. *International Journal of Medical Toxicology and Forensic Medicine*. 2026; 16:E53384.



<https://doi.org/10.22037/ijmtfm.v16.53384>

Article info:

Received: 07 September, 2026

Accepted: 23 September, 2026

Published: 13 October, 2026

Keywords:

Dhole optimization algorithm, Multi-objective optimization, Unmanned underwater vehicle, Task allocation, Saturation-aware allocation, Pareto archive

ABSTRACT

Background: Underwater forensic investigations frequently involve searching, locating, and recovering submerged human remains and associated forensic evidence under challenging environmental conditions. Efficient coordination of multiple unmanned underwater vehicles (UUVs) can support forensic investigators by reducing search time, improving spatial coverage, and limiting unnecessary energy consumption during underwater recovery operations. This study proposes a Multi-Objective Dhole Optimization Algorithm (MO-DOA) for discrete saturation-aware allocation.

Methods: The method maps each candidate to a continuous latent score matrix, decodes it to UUV-to-region assignments, repairs assignment and saturation violations, and uses Pareto dominance with a diversity-preserving external archive to select leaders for the Dhole Optimization Algorithm search, encircling, and attack phases.

Results: Evaluation uses an 800 m × 500 m maritime benchmark with eight UUVs, four clustered target regions, and three inaccessible reef zones. In the supplied 20-run results package, MO-DOA attained HV = 0.921, IGD = 0.048, mission effectiveness = 93.8, energy/travel cost = 142.6, threat exposure = 0.220, saturation deviation = 0.50, and runtime = 10.7 s, outperforming CEA, Improved WOA, MDO, IMM-P-GWO, and IPSO-VP on the reported criteria. Convergence curves show earlier improvement and sustained Pareto-front quality.

Conclusion: The findings support MO-DOA as a compact Pareto-based allocation framework, subject to final verification of the supplied run-level statistics.

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Introduction

Unmanned underwater vehicles (UUV) fleets are increasingly used for marine sensing, inspection, search, monitoring, and defense because multiple vehicles can cover separated regions without exposing human operators to underwater hazards [1, 2]. Their effectiveness, however, depends on task allocation and navigation. An effective allocation must place heterogeneous vehicles where they provide high mission value while limiting travel cost and threat exposure, and meeting minimum and maximum region-level saturation requirements. Prior work has addressed cooperative and autonomous underwater vehicle (AUV) path planning with multi-objective particle-swarm optimization [3], multi-regional coverage through co-evolution [4], formation learning under uncertainty [5], and dynamic allocation for heterogeneous UUV swarms [6]. Distributed control and consensus studies further show that swarm performance depends on interaction topology, information exchange, and reconfiguration ability [7-9]. Many allocation formulations nevertheless rely on scalarized objectives or treat assignment separately from operational feasibility. Fixed weights can hide trade-offs that are important to a mission planner. The Dhole Optimization Algorithm (DOA) models dynamic pack formation, vocalization-guided switching, searching, encircling, and coordinated attack [10]. Its original formulation is single-objective and explicitly identifies multi-objective extension as future work. Multi-Objective Dhole Optimization Algorithm (MO-DOA) addresses that gap for categorical UUV assignment by combining latent continuous encoding with Pareto-aware leadership, external archiving, diversity maintenance, and deterministic feasibility repair. The main contribution is therefore not a new weighted cost function, but a multi-objective DOA search process that preserves four mission criteria as separate objectives and returns a set of feasible nondominated allocations.

Multi-objective swarm optimizers require mechanisms beyond the single-objective update rule: nondomination ranking, retention of elite solutions, and diversity control. MOGWO, for example, selects leaders from a nondominated archive and promotes sparsely occupied regions [11], while recent constrained robot planning demonstrates the usefulness of Pareto search with diversity preservation [12]. MO-DOA adopts these multi-objective principles but retains DOA-specific search dynamics. The research problem is thus threefold: continuous DOA motion must be translated into categorical UUV assignments; scalar prey quality must be replaced by Pareto-aware leader

selection; and aggressive updates must not violate one-UUV/one-region assignment or saturation bounds.

Materials and Methods

Saturation-Aware Task-Allocation Model

Consider a swarm of N unmanmanned underwater vehicles (UUVs), denoted by

$$\mathcal{U} = \{1, \dots, N\},$$

and M mission regions,

$$\mathcal{R} = \{1, \dots, M\}.$$

Let x_{ir} be a binary decision variable indicating whether UUV i is assigned to mission region r . Each UUV is assigned to exactly one primary region during an allocation cycle. Let n_r denote the number of UUVs assigned to region r . To ensure adequate mission coverage while preventing excessive concentration of vehicles, the number of UUVs allocated to each region is constrained by predefined lower and upper saturation bounds, L_r and U_r , respectively:

$$\begin{aligned} x_{ir} &\in \{0, 1\}, \quad \sum_{r=1}^M x_{ir} = 1, \quad \forall i \in \mathcal{U}, \\ L_r &\leq n_r = \sum_{i=1}^N x_{ir} \leq U_r, \quad \forall r \in \mathcal{R}. \end{aligned} \quad (1)$$

Each feasible allocation is evaluated using four mission-level objectives: mission effectiveness, energy and travel cost, threat exposure, and saturation deviation. The resulting multi-objective vector is expressed as

$$F(x) = [-E(x), C(x), R(x), S(x)], \quad (2)$$

where mission effectiveness $E(x)$ is maximized, whereas energy/travel cost $C(x)$, threat exposure $R(x)$, and saturation deviation $S(x)$ are minimized. The negative sign applied to $E(x)$ allows all objectives to be handled consistently within a minimization-based Pareto-dominance framework.

For region r , let ρ_r denote the normalized target density and v_r the normalized mission or strategic value. Let a_i represent the normalized operational capability of UUV i . The mission benefit associated with assigning UUV i to region r is defined as

$$g_{ir} = w_\rho \rho_r + w_v v_r + w_a a_i,$$

where w_ρ , w_v , and w_a are nonnegative weighting

coefficients satisfying

$$w_p + w_v + w_a = 1.$$

The four objective functions are then defined as

$$\begin{aligned} E(x) &= \frac{100}{N} \sum_{i=1}^N \sum_{r=1}^M x_{ir} g_{ir}, \\ C(x) &= \sum_{i=1}^N \sum_{r=1}^M x_{ir} (e_i d_{ir} + c_{ir}), \\ R(x) &= \frac{1}{N} \sum_{i=1}^N \sum_{r=1}^M x_{ir} q_r h_i, \\ S(x) &= \frac{1}{M} \sum_{r=1}^M \frac{|n_r - m_r|}{\max(1, m_r)}. \end{aligned} \quad (3)$$

Here, d_{ir} denotes the travel distance from UUV i to region r , e_i is the corresponding energy-consumption coefficient per unit distance, and c_{ir} represents any additional transition cost. The variable q_r characterizes the normalized threat level associated with region r , while h_i denotes the vulnerability of UUV i . The preferred saturation level of region r is denoted by m_r , where $m_r \in [L_r, U_r]$.

To ensure feasibility, a deterministic repair mechanism is applied before evaluating the objective. The repair process first ensures that every UUV is assigned to exactly one mission region. If a region is under-saturated, a UUV is transferred from a donor region satisfying $n_r > L_r$. The donor vehicle is selected according to the smallest increase in normalized travel cost and threat exposure. Similarly, when a region exceeds its upper saturation limit, surplus UUVs are reassigned to feasible recipient regions using the same incremental-cost criterion. Consequently, all objective values are calculated only after the candidate allocation satisfies the assignment and saturation constraints.

MO-DOA Search, Archive, and Feasibility Control

The proposed Multi-Objective Dhole Optimization Algorithm (MO-DOA) represents each candidate dhole k using a continuous latent score matrix

$$Z^{(k)} \in \mathbb{R}^{N \times M}.$$

Each row of the matrix corresponds to a UUV,

whereas each column represents a mission region. The continuous representation enables the original DOA search operators to be applied without directly performing arithmetic operations on categorical region identifiers.

For each UUV i , the corresponding discrete assignment is obtained by selecting the region associated with the largest latent score in row i :

$$x_{ir} = 1 \text{ iff } r = \arg \max_{j \in \{1, \dots, M\}} Z_{ij}. \quad (4a)$$

The decoded allocation is subsequently processed by the feasibility-repair mechanism described above.

Population Initialization and External Archive

The initial population consists of randomly generated latent score matrices. Each candidate is decoded into a discrete UUV allocation, repaired to satisfy the assignment and saturation constraints, and evaluated according to the four-objective vector in Eq. (2). Pareto dominance is then applied to classify the population, and all feasible nondominated candidates are stored in an external archive A . MO-DOA employs both local and global archive information to guide the search. A local prey solution, P_{local} , is selected from an appropriate nondominated neighborhood, whereas a global prey solution, P_{global} , is sampled from a sparsely occupied region of the external archive. The prey representation used to guide the latent search is

$$P = \frac{P_{\text{local}} + P_{\text{global}}}{2}. \quad (4b)$$

This mechanism allows the search to exploit locally competitive solutions while simultaneously encouraging exploration of less crowded portions of the Pareto front.

Dynamic Pack Size and Vocalization-Based Search Control

MO-DOA retains the dynamic pack-size and vocalization-guided switching mechanisms of the original Dhole Optimization Algorithm [10]. At each iteration, the pack-member number (PMN) is generated as

$$PMN = \text{round}(15r_1 + 5),$$

where $r_1 \sim U(0, 1)$. Thus, the effective pack size varies between 5 and 20.

A time-dependent coefficient C_2 controls the magnitude of the search movement:

$$C_2 = 1 - \frac{t}{T},$$

where t is the current iteration and T is the maximum number of optimization iterations.

A vocalization variable $v \sim U(0, 1)$ determines the behavioral phase. When $v < 0.5$, the algorithm performs either searching or encircling depending on the sampled pack size. When $v \geq 0.5$, the algorithm enters the attack stage.

The searching operation is defined as

$$Z_i^{t+1} = Z_i^t + C_2 r_2 (P - Z_i^t),$$

where $r_2 \sim U(0, 1)$. The encircling update is

$$Z_i^{t+1} = Z_i^t - Z_z^t + P, \quad (5)$$

where Z_z^t denotes the latent position of a randomly selected dhole $z \neq i$. The search operator moves a candidate progressively toward prey information, while the encircling operator introduces a larger population-dependent perturbation that can improve exploration.

Pareto-Controlled Attack Stage

The attack stage retains the basic structure of the original DOA while replacing its scalar fitness-based control mechanism with a temporary Pareto-aware control quantity. This modification is necessary because MO-DOA evaluates each allocation using a vector of conflicting objectives rather than a single scalar fitness value.

For candidate i , the temporary Pareto control loss is defined as

$$\psi_i = \text{rank}_i + \frac{1}{1 + CD_i} + \text{penalty}_i,$$

where rank_i is the nondomination rank, CD_i is the crowding distance, and penalty_i represents any repair-related penalty. Lower values of ψ_i therefore correspond to more favorable candidates.

The prey-size controller is then calculated as

$$S_i = \frac{3r_3 \psi_i}{\psi_{\text{prey}} + \varepsilon}, \quad (6)$$

where $r_3 \sim U(0, 1)$, ψ_{prey} denotes the corresponding control value of the selected prey, and ε is a small positive constant used to prevent division by zero.

The value of S_i determines which attack mechanism is activated. For larger prey-size values, the original DOA's weakened-prey cosine-sine attack is employed; otherwise, the immediate global-prey attack is performed [10].

Archive Updating and Termination

After every searching, encircling, or attacking operation, the updated latent score matrix is restricted to its allowable range and decoded into a discrete UUV-to-region allocation. The resulting allocation is repaired, evaluated using Eq. (2), and merged with the existing archive.

Pareto dominance is subsequently applied to identify the updated nondominated set, while the grid-based diversity mechanism maintains a well-distributed archive when its capacity is exceeded. This iterative process continues until the maximum number of iterations is reached.

For the present benchmark, $T = 200$.

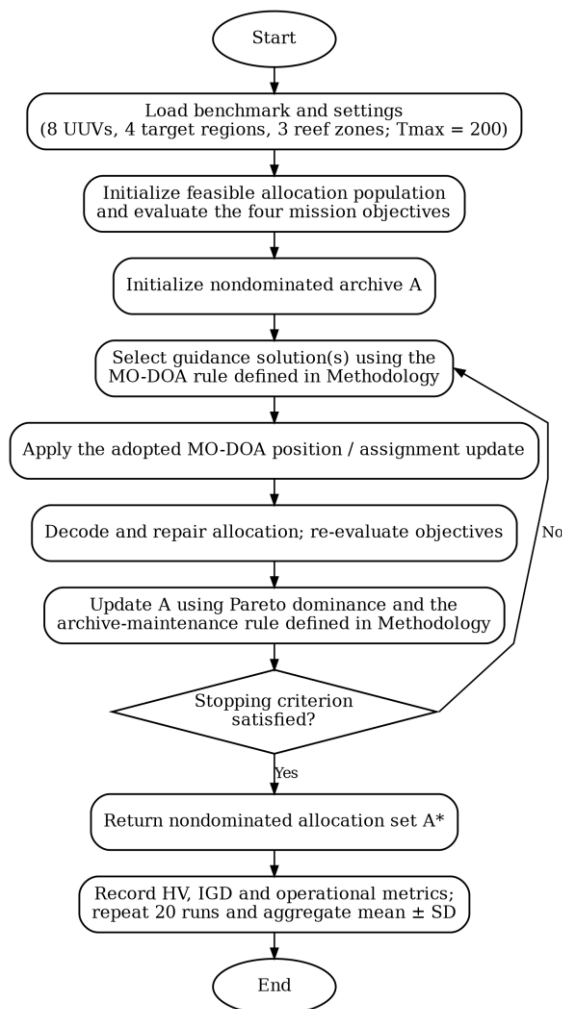
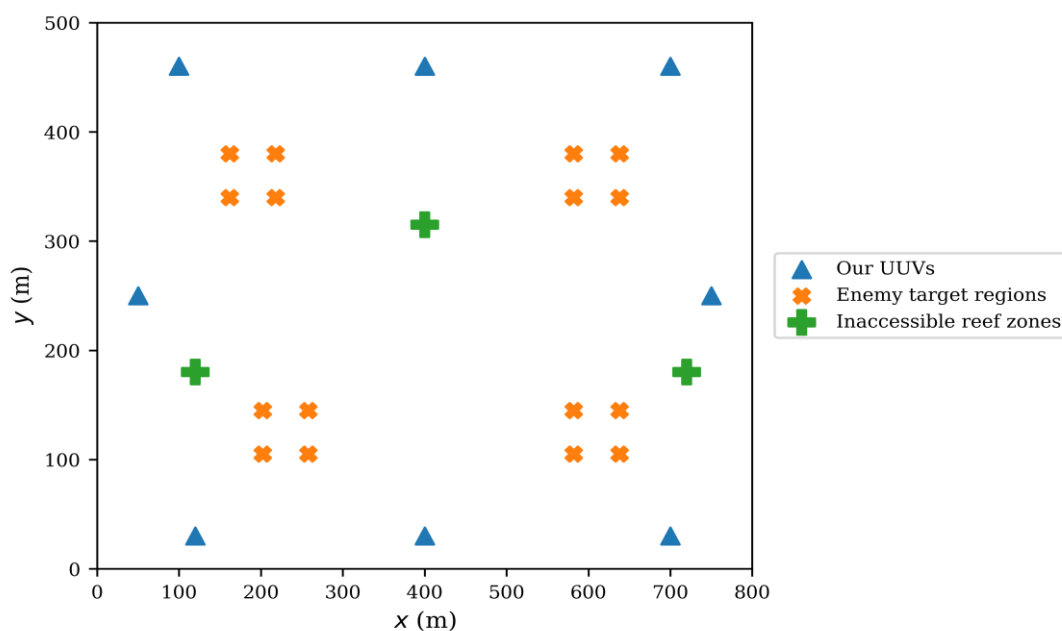
During optimization, Hypervolume (HV) and Inverted Generational Distance (IGD) are recorded to characterize convergence and Pareto-front quality. At termination, the final nondominated allocation archive A^* is returned. The complete optimization procedure is independently repeated 20 times to evaluate robustness and stability, and the resulting performance measures are summarized using the corresponding mean and standard-deviation statistics (Figure 1).

Results

Benchmark and Evaluation Protocol

The benchmark spans $800 \text{ m} \times 500 \text{ m}$ and contains eight UUV start positions, four clustered hostile target regions, and three inaccessible reef zones (Figure 2). All methods use the same geometry, target distribution, saturation constraints, four objective definitions, and a 200-iteration horizon. MO-DOA is compared with CEA, Improved WOA, MDO, IMMP-GWO, and IPSO-VP. Hypervolume (HV; higher is better) and inverted generational distance (IGD; lower is better) measure Pareto-front quality; mission effectiveness, energy/travel cost, threat exposure, saturation deviation, and runtime provide operational comparison. Stability summaries use 20 runs.

The supplied revised results package reports the numerical values and convergence curves used below. It also states that the MO-DOA scenario values and summary-statistical significance calculations require final validation against archived seed-matched run

International Journal of
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Medical Toxicology & Forensic Medicine**Figure 2.** Experimental configuration in the two-dimensional maritime space.

outputs. Accordingly, the manuscript reproduces the supplied results without converting those provisional inferential statistics into stronger claims.

Comparative Performance

MO-DOA ranks first on all seven reported criteria (Table 1). Relative to the nearest competitor, CEA, HV increases from 0.905 to 0.921 (about 1.77%) and mission effectiveness from 92.9 to 93.8 (0.97%), while IGD decreases by about 12.73%, energy/travel cost by 2.86%, threat exposure by 3.51%, and saturation deviation by 13.79%. Runtime is 10.7 s, 23.02% below CEA and slightly below IPSO-VP, the next-fastest method.

Stability and Convergence

The 20-run summary (Table 2) is consistent with the endpoint ranking. MO-DOA reports $HV=0.921\pm0.008$ and $IGD=0.048\pm0.005$. Against CEA, the supplied effect sizes are $d=1.88$ for HV and $d=1.40$ for IGD, with approximate two-sided Welch tests reported as $p<0.001$. Larger standardized separations are reported for the remaining baselines. Figures 3 and 4 show that MO-DOA enters the high-HV region earlier, remains above the comparators, and reduces IGD more rapidly, with no late-iteration reversal in the displayed 200-iteration horizon.

Figures 3 and 4 show the same 200-iteration ordering: MO-DOA enters the high-HV region earlier and remains above the baselines, while its IGD decreases more rapidly and finishes at the smallest reported distance. CEA is consistently the nearest competitor, followed by Improved WOA, MDO, IMMP-GWO, and IPSO-VP.

Table 1. Comparative results for the UUV saturation-attack task-allocation benchmark.

Algorithm	HV $\uparrow$	IGD $\downarrow$	Mission effectiveness $\uparrow$	Energy/travel cost $\downarrow$	Threat exposure $\downarrow$	Saturation deviation $\downarrow$	Runtime (s) $\downarrow$
MO-DOA	0.921	0.048	93.8	142.6	0.220	0.50	10.7
CEA	0.905	0.055	92.9	146.8	0.228	0.58	13.9
Improved WOA	0.877	0.072	90.8	151.5	0.249	0.69	11.7
MDO	0.868	0.078	90.1	154.2	0.256	0.74	12.1
IMMP-GWO	0.851	0.089	88.3	159.7	0.271	0.81	14.6
IPSO-VP	0.812	0.117	85.6	167.9	0.298	1.05	10.9

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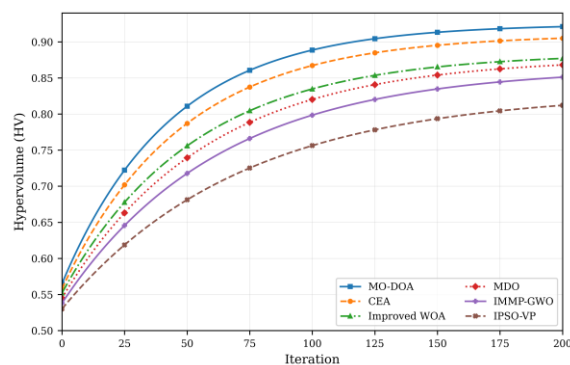
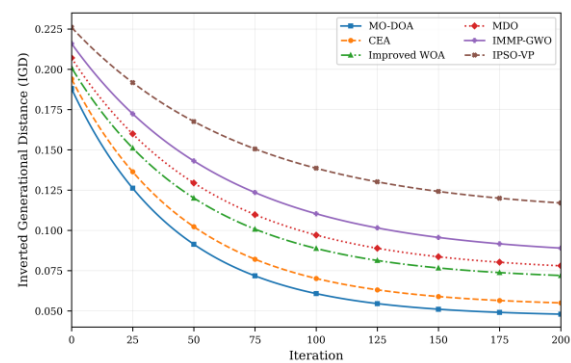
Note: $\uparrow$ higher is better; $\downarrow$ lower is better. Values are reproduced from the supplied revised results package.

Table 2. Twenty-run stability and significance analysis relative to MO-DOA.

Algorithm	HV (mean $\pm$ SD)	IGD (mean $\pm$ SD)	p(HV) vs MO-DOA	d(HV)	p(IGD) vs MO-DOA	d(IGD)
MO-DOA	0.921$\pm$0.008	0.048$\pm$0.005	—	—	—	—
CEA	0.905 $\pm$ 0.009	0.055 $\pm$ 0.005	<0.001	1.88	<0.001	1.40
Improved WOA	0.877 $\pm$ 0.011	0.072 $\pm$ 0.006	<0.001	4.57	<0.001	4.35
MDO	0.868 $\pm$ 0.012	0.078 $\pm$ 0.007	<0.001	5.20	<0.001	4.93
IMMP-GWO	0.851 $\pm$ 0.013	0.089 $\pm$ 0.008	<0.001	6.49	<0.001	6.15
IPSO-VP	0.812 $\pm$ 0.018	0.117 $\pm$ 0.011	<0.001	7.83	<0.001	8.08

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Note: Supplied p-values are approximate two-sided Welch-test results from displayed summary statistics (n=20); d is pooled-SD Cohen's. Run-level recomputation is required for final inference.

International Journal of
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Medical Toxicology & Forensic Medicine**Figure 4.** Inverted Generational Distance (IGD) convergence across 200 iterations.

Discussion

The reported advantage is consistent across Pareto quality and mission-level criteria rather than being produced by a single favorable metric. The gain over CEA is modest for HV and mission effectiveness but larger for IGD and saturation deviation, suggesting that the principal benefit is improved front proximity and allocation balance. The convergence profiles also indicate that the final ranking is not driven solely by late improvement. Within this fixed implementation, MO-DOA combines the best reported quality with the

lowest runtime; runtime should nevertheless be interpreted as benchmark-specific because it depends on hardware, software, and implementation details. The evidence has important limits. Only one 800 m $\times$ 500 m scenario is supplied, with eight UUVs, four target regions, and three reef zones. No sensitivity study is available for fleet size, target density, saturation bounds, threat uncertainty, population size, or alternative evaluation budgets. The results package also lacks hardware/software versions and complete optimizer settings. Most importantly, the reported p-values are calculated from displayed means and standard deviations rather than raw seed-matched

records. Final inferential reporting should therefore recompute tests and confidence intervals from the archived run-level outputs and document the execution environment.

Conclusion

MO-DOA extends the single-objective Dhole Optimization Algorithm to saturation-aware multi-UUV task allocation using latent score encoding, Pareto-dominance selection, a diversity-preserving archive, sparse-region leaders, and deterministic feasibility repair. In the supplied benchmark results, it provides the strongest reported balance of Pareto quality, mission effectiveness, operational cost, risk, saturation balance, and runtime among the six compared methods, with convergence trends that support the endpoint ranking. Broader scenario testing and verification from raw repeated-run records remain necessary before the performance claims can be generalized.

Ethical Approval

Not applicable.

Acknowledgment

The authors thank the Department of Computer Science and Engineering and the Department of Computer Science and Technology, Madanapalle Institute of Technology and Science, Andhra Pradesh, India, for technical and computational support.

Funding

No external funding was received for this research.

Conflicts of Interest

The authors report there are no competing interests to declare.

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