A NEW COMPUTATIONAL INTELLIGENCE MODEL BASED ON FUSION OF BAT ALGORITHM (BA) AND GREY WOLF OPTIMIZER (GWO) TO IMPROVE A DEEP CNN CLASSIFIER APPLIED FOR RECOGNITION OF GROUND AND AIR MILITARY VEHICLES

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This paper proposes a new computational intelligence model based on the combination of Bat Algorithm (BA) and Grey Wolf Optimizer (GWO) applied to optimize the performance of the Deep Convolutional Neural Network (CNN) classifier for Automatic Target Recognition (ATR). We have evaluated the performances of the model for classification of ground and air military vehicles in SAR and optical imagery, using two datasets: MSTAR (Moving and Stationary Target Acquisition) dataset and Military and Civilian Vehicles dataset. We have considered the Residual Neural Net (ResNet-18) as a classifier. For MSTAR SAR image dataset, one obtains an accuracy of 93.22% for the combination BA-GWO-ResNet, versus 83.84% using only a standalone ResNet classifier. For Military and Civilian Vehicles optical image dataset, one obtains an accuracy of 94.73% for the cascade BA-GWO-ResNet versus a score of 93.90%, when one uses a ResNet classifier. We point out that the proposed model directly performs only classification itself, without requiring a processing phase for object detection.

Keywords: Automatic Target Recognition (ATR), Bat Algorithm (BA), Grey Wolf Optimizer (GWO), Deep CNN Classification, Moving and Stationary Target Acquisition and Recognition (MSTAR), Synthetic Aperture Radar (SAR), Military and Civilian Vehicles Classification.

1. Introduction

The optimization of deep learning models is an important step in achieving high performance in tasks involving image recognition and classification. Traditional optimization methods, such as stochastic gradient descent (SGD) and its variant (Adam), have proven effective in training deep architectures [1]. Deep learning models are sensitive to hyperparameter settings, such as learning rate, batch size, and weight decay. They have a direct impact on the convergence and generalization of the models. To address this challenge, numerous metaheuristic

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algorithms have been used for the automation of the hyperparameter tuning since these algorithms provide efficient global search capabilities. The most widely used algorithms include Particle Swarm Optimization [2], Genetic Algorithms [3], and more recent techniques such as the Grey Wolf Optimizer (GWO) [4] and Bat Algorithm (BA) [5]. These strategies have been successfully applied to optimize convolutional neural networks (CNNs), demonstrating improvements in accuracy, and training efficiency compared to manual or other types of search methods [6].

Deep CNNs are the most performant algorithms nowadays for vehicle recognition in aerial and ground imagery, but their performance relies heavily on the chosen architecture of the network. Meta-heuristics like BA and GWO offer gradient-free global search, making them attractive for noisy training conditions. Integrating swarm intelligence strategies help navigate the complex space of architectures and hyperparameters, improving generalization and reducing sensitivity to imbalance or varying sample sizes. Recent CNN models that combine convolutional features with dictionary-learning refinements have achieved near-perfect accuracy on MSTAR [7].

This paper extends the recent work of the same authors previously presented in [8], where the original hybrid BA-GWO was introduced for optimizing a ResNet classifier on the MSTAR SAR dataset. In the current paper, we propose an improved BA-GWO framework featuring an immigration strategy, a composite multi-criteria objective function, and a multi-fidelity evaluation scheme. The experimental results demonstrate superior performance on the MSTAR dataset. Additionally, the improved classifier is tested also on the Military and Civilian Vehicles Classification [9] dataset. The final goal is to optimize a ResNet-18 architecture, maximizing its test accuracy, while maintaining a competitive execution time. The experimental results show that our proposed algorithm outperforms the standard ResNet-18 model, achieving higher classification accuracy for both datasets. The proposed optimization algorithm is based on the BA introduced by Xin-She Yang in [10]. In the literature, several BA variants have been developed to improve performance, such as those presented in [11], [12]. In our work, BA is enhanced through the integration of a hierarchical social structure inspired by the GWO, an algorithm originally proposed by S. Mirjalili, S. M. Mirjalili, and A. Lewis in [13]. This hybrid BA-GWO algorithm combines GWO's strong global search ability with BA's local exploitation strengths, enabling more effective fine tuning of the key hyperparameters in the ResNet classifier.

Our main personal contributions are the following:

- A novel hybrid BA-GWO with leadership hierarchy and local exploitation, improved with an immigration strategy. The worst-ranked agents are replaced with new, randomly sampled agents, while the top three are protected. Each immigrant is fully evaluated before insertion. This maintains population diversity and mitigates premature convergence.

- The objective function optimized by the hybrid BA-GWO is a composite function that explicitly balances accuracy and class balance, while also penalizing overfitting.
- To reduce computational complexity, the algorithm uses a three-stage process. Candidates are first tested on reduced training sets with smaller models to quickly eliminate the weak architecture. Strong candidates are then re-evaluated under increased training sets, ending with the complete dataset.
- The optimization of key ResNet hyperparameters: learning rate, batch size, optimizer type, and activation function.

2. Theoretical framework

Deep CNNs are very successful models in image classification tasks, mainly due to their ability to learn hierarchical feature representations from the raw pixels, unlike traditional models which require an explicit feature selection step. Increasing the depth of the CNNs often leads to optimization issues, such as the vanishing gradient problem [14], where the magnitude of the gradients becomes too small for updating the weight.

He et al. introduced the Residual Network (ResNet) models [15] to mitigate this problem. This is done by remodeling the layers as residual functions with identity shortcuts. This design allows gradients to flow more effectively through the network, enabling the successful training of deep models [15].

The ResNet-18 variant used in this work is a lightweight residual network with four stages of residual blocks, offering an effective balance between accuracy and computational cost for moderate-sized datasets. Hybrid methods that pair CNN features with classifiers like SVM or k-NN also achieve strong results with lower complexity [16], and multi-scale convolutional fusion has proven effective for SAR target recognition by enriching feature representation [17]. In our study, we adopted a tailored fusion of two swarm-intelligence algorithms to optimize this ResNet.

BA is a part of the swarm intelligence class of algorithms which are nature-inspired metaheuristic optimization algorithms. It is based on the echolocation behavior of microbats which use pulses to navigate and detect prey in complete darkness. The algorithm aims at modelling this behavior into a mathematical model for solving complex optimization problems [10]. In BA, each bat represents a candidate solution in the search space. The agents move randomly based on a set of parameters: v_i^t (velocity), x_i^t (position), f_i (frequency), A_i (loduness), r_i (pulse rate). The search process evolves with each iteration where each bat adjusts its movement towards promising regions of the search space according to the following equations.

$$f_i = f_{min} + (f_{max} - f_{min})\beta \tag{1}$$

$$v_i^t = v_i^{t-1} + (x_i^{t-1} - x_*)f_i \tag{2}$$

$$x_i^t = x_i^{t-1} + v_i^t \tag{3}$$

Where f_{min} and f_{max} are the ranges of the frequencies, β is a random variable in [0, 1] and x_* is the current best solution.

An additional random walk is applied to the best solution.

$$x_{new} = x_* + \varepsilon A^t \tag{4}$$

The loudness (A_i) and pulse rate (r_i) are dynamically updated as the bat approaches its prey (i.e. the optimal solution), according to relations

$$A_i^{t+1} = \alpha \cdot A_i^t \tag{5}$$

$$r_i^{t+1} = r_i^o(1 - e^{-\gamma t}), \tag{6}$$

where the real parameters α and γ belong to interval (0,1), controlling the reduction of loudness and the increase of pulse emission rate over time. As iterations proceed, the loudness decreases, and the pulse emission rate increases, allowing the algorithm to gradually switch from global exploration to local exploitation.

A newly generated solution x_{new} replaces the current solution x_i if it achieves a lower objective function value, i.e. if $f(x_{\text{new}}) < f(x_i)$.

GWO is a nature-inspired metaheuristic algorithm firstly proposed in [13]. It models the social hierarchy and cooperative hunting strategy of grey wolves in nature. The algorithm's main strengths lie in its simplicity and its well-balanced trade-off between exploration and exploitation, achieved through leadership hierarchy and adaptive encircling of the prey. In the GWO population, each search agent represents a potential solution in an n-dimensional space. The wolves are categorized according to a leadership hierarchy: α (alpha): the best solution found so far (leader), β (beta), δ (delta), ω (omega). The optimization process simulates three main stages of hunting: encircling prey, hunting, and attacking. The equations of this algorithm are described in [13].

3. Novel BA-GWO Algorithm

We propose a novel hybrid metaheuristic that combines BA for adaptive local exploitation with GWO for structured global exploration [4]. The goal is to tune the key hyperparameters of a ResNet classifier efficiently in its complex search space. This hybrid algorithm leverages BA's loudness–pulse dynamics to refine promising areas while GWO's leadership hierarchy structure guides the population toward globally competitive regions.

Initially, we have chosen to optimize the following hyperparameters due to high impact on training dynamics and generalization:

- Learning rate which controls the update step size and determines convergence speed and stability, in the range of [1e-5, 1e-3].

- Batch size which influences gradient noise and estimation stability. This is a continuous range: [32, 256].
- Activation function which affects the gradient flow. It is a set containing the following activation functions {ReLU, LeakyReLU, ELU, Tanh}.

An initial population of N agents is sampled uniformly within the bounds. For each candidate solution x, a ResNet is trained with the corresponding hyperparameters and the validation loss is computed. Validation loss is the objective to be minimized.

At each iteration, agents are ranked by their fitness. The top three ones form the leadership group, {α, β, δ}, as described in the original GWO. For any agent i, the GWO position update uses the mean attraction to these leaders with time-varying coefficients that decrease linearly, thus decaying exploration and increasing exploitation as iterations progress. Finally, each iteration consists of 3 distinct phase: ranking the agents, GWO updating mechanism, and BA refinement and acceptance of the best solution.

The main advantages of this approach are the efficient exploration using the GWO leadership mechanism, the adaptive refinement using BA and the robustness to local optima, mitigating premature convergence and improving the final validation loss.

4. Improved BA-GWO with Immigration and Composite Objective

Although the baseline BA-GWO achieves competitive results, it remains prone to population stagnation and may exhibit unstable behaviour when applied to more complex deep learning problems. To address these limitations, we have designed an improved version of the initial BA–GWO proposed by us in [8]. The extended framework has been specifically developed based on the observed limitations described in the following table:

Table 1

Improved BA-GWO Problems and the corresponding solutions

Identified Problem	**Solution in Improved BA-GWO**
Limited population diversity often leads to premature convergence and suboptimal exploration of the search space.	Introduction of an immigration strategy that periodically replaces the weakest agents with newly generated candidates, thus maintaining population diversity and preventing stagnation.
Traditional single-metric fitness functions fail to capture the multifaceted nature of model performance and generalization.	Design of a composite objective fitness function that represents the true optimization complexity.
Exhaustive full-fidelity evaluations of all candidates significantly increase computational cost.	Implementation of a multi-fidelity racing scheme that evaluates candidates progressively across increasing fidelity levels, allowing early elimination of weak configurations and efficient use of computational resources.

The search space in the improved BA–GWO has also been extended to also include the optimizer type. The optimizer is selected from {Adam, AdamW, Lion} [18].

One of the major changes to the initial BA-GWO algorithm is the new fitness function. The fitness function is defined based on the F1-score, balanced accuracy, the area under the receiver operating characteristic curve (AUROC), and it also includes a penalty for overfitting. The objective is to maximize the following score S.

$$S = 0.5\, F1_{\text{macro}} + 0.3\, BA_{acc} + 0.2\, \text{AUROC}_{MACRO} - 0.25\, max\left(0, Acc_{train} - Acc_{val}^{bal}\right) \tag{7}$$

$$\text{F1}_{\text{macro}} = \frac{1}{K}\sum_{k=1}^{K}\frac{2P_kR_k}{P_k+R_k} \tag{8}$$

$$\text{BAcc} = \frac{1}{K}\sum_{k=1}^{K}\text{TPR}_\text{k} \tag{9}$$

$$\text{TPR}_\text{k} = \frac{TP_k}{TP_k+FN_k} \tag{10}$$

$$\text{AUROC}_{\text{macro}} = \frac{1}{K}\sum_{k=1}^{K}\text{AUC(ROC of class } k \text{ vs. rest)} \tag{11}$$

where Acc_{train} is the accuracy of training; Acc_{val}^{bal} is validation balanced accuracy. BAcc is the balanced accuracy; AUROC_{MACRO} is the macro-averaged Area Under the Receiver Operating Characteristic curve.

To reduce computational complexity, the optimization proceeds in three stages. Stage 1 uses as a low-resolution filtering, a small fraction of the data (only 15%), and a limited number of epochs. The goal of this stage is to remove as soon as possible the weak solutions. Stage 2 increases data usage to 50% and refines the strong solutions. Stage 3 uses the full dataset and complete resolution of the data to obtain the final convergence. Only the best configurations from each stage are kept to the next, effectively using the resources only on the most relevant solutions.

An important improvement in this variant is the immigration mechanism, where a fraction of the worst solutions is replaced with newcomers, while the top three solutions are always preserved. Each immigrant is evaluated, helping maintain diversity and sustain exploration. Each iteration begins with a GWO based movement mechanism toward the leader agents. BA refinement uses adaptive frequency and pulse-rate to increase the exploitation phase as the optimization algorithm proceeds.

After the three-stage process, the best configuration is retrained on the full dataset.

5. Datasets

The experiments have been performed on two international datasets, namely the Moving and Stationary Target Acquisition and Recognition (MSTAR) and the Military and Civilian Vehicles dataset.

The MSTAR dataset is one of the most widely used collection of SAR images [19]. It contains high-resolution SAR imagery depicting a set of different types of military ground vehicles captured under different conditions, including different angles and aspect orientations. These variations make it an important benchmark for evaluating the performances of ATR models.

Attention-enhanced CNNs using coordinate-based focus mechanisms have obtained over 95% accuracy on MSTAR [5]. In other studies, different dataset splits have led to notable differences in reported accuracies. Variations in dataset splits lead to differing results: for example, the CCAM network achieved 95.8% [20]. Our study uses a very small training fraction and a different configuration and still it reaches 93.74% accuracy, indicating a very high performance under constrained conditions. We used a subset of the MSTAR/IU Mixed Targets dataset [21], which includes eight vehicle classes. Each class corresponds to a different military vehicle. A detailed description of each class can be seen in table 2.

Table 2

MSTAR dataset classes

Class name	Description
2S1	Soviet 122 mm self-propelled howitzer based on a tracked chassis; provides mobile artillery support with good cross-country mobility.
BRDM_2	Soviet 4×4 amphibious armored reconnaissance vehicle equipped with a turret-mounted 14.5 mm heavy machine gun; used for scouting and patrol.
BTR_60	Early Soviet 8×8 armored personnel carrier capable of transporting infantry under armor protection; amphibious and lightly armed.
D7	Military bulldozer (based on the Caterpillar D7) used for engineering tasks such as clearing obstacles, fortifications, and road construction.
SLICY	The "Slicy" target is a precisely designed and machined engineering test target containing standard radar reflector primitive shapes such as flat plates, dihedrals, trihedrals, and top hats.
T62	Soviet main battle tank introduced in the 1960s with a 115 mm smoothbore gun and improved armor compared to earlier T-55 models.
ZIL131	Soviet 6×6 general-purpose military truck used for transport, communications, and as a chassis for various equipment.
ZSU_23_4	Self-propelled, radar-guided anti-aircraft gun system armed with four 23 mm autocannons; effective against low-flying aircraft.

Representative SAR samples from each class are displayed in Fig. 1 below. The Military and Civilian Vehicles dataset was specifically created to support research in automatic target recognition (ATR) and object detection tasks involving both military and civilian targets [9]. We have restricted the dataset to military-related classes only, resulting in 4487 samples belonging to the following classes: military trucks, military tanks, military aircraft, and military helicopters (Fig. 2).

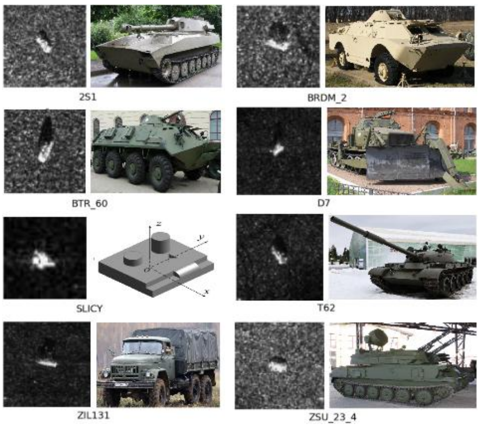

Fig. 1. Examples of instances per class for the MSTAR dataset [22]

Fig. 2. Examples of instances per class for the Military and Civilian Vehicles dataset

In this paper, a balanced portion of the dataset was used to evaluate the performance and generalization capability of the proposed BA–GWO optimization algorithms. The presence of both ground and airborne vehicles introduces significant intra-class and inter-class variability. This diversity makes the dataset particularly well suited for assessing the adaptability of the proposed approach to operationally realistic target recognition scenarios.

6. Experimental results

This section compares the improved BA–GWO–ResNet with the baseline ResNet on the two datasets described previously. All models were trained under identical settings, using the MSTAR split of 9% training, 1% validation, and 90% testing.

The standalone ResNet (i.e. no architecture optimization performed) achieved 83.84% accuracy. Adding the initial BA–GWO optimization raised the accuracy to 91.6%, while also reducing training time. Finally, our improved BA–GWO–ResNet, further increased the accuracy to 93.22% (Table 3). Despite the extra complexity, its training time remained competitive.

These results demonstrate the benefits of integrating swarm intelligence algorithms with deep model optimization. The proposed improved BA-GWO-ResNet resulted in 9.38% improvement over the standalone ResNet in accuracy, demonstrating its effectiveness in hyperparameter search (Table 3, Fig. 3).

Table 3

Results of the MSTAR Dataset

Model	**Training Time (s)**	**Accuracy (%)**
ResNet	70.34	83.84
BA-GWO-ResNet	56.72	91.60
Improved BA-GWO-ResNet	59.64	93.22

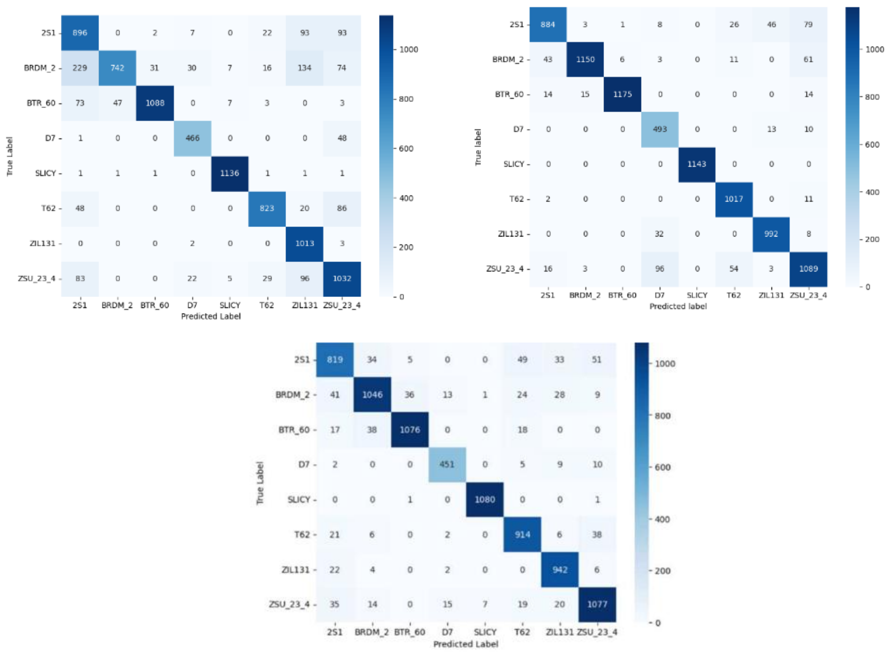

Fig. 3. Confusion matrix for the MSTAR dataset using the standalone ResNet (left), BA-GWO-ResNet (middle), Improved BA-GWO-ResNet (right)

To further analyze the effects of the optimization, the best hyperparameters found for each configuration are summarized in Table 4.

Table 4

Resulting parameters for the MSTAR dataset

Model	**Batch Size**	**Learning Rate**	**Activation Function**	**Optimizer**
ResNet	128	1.0×10^{-4}	ReLU	AdamW
BA-GWO-ResNet	38	8.05×10^{-5}	ELU	AdamW
Improved BA-GWO-ResNet	128	3.87×10^{-4}	LeakyReLU	Lion

The Military and Civilian Vehicles Classification dataset [9] is a more complex challenge due to the increased intra-class. After extracting only the military vehicles, the dataset was divided into 70% training, 15% validation, and 15% testing. For this dataset, experiments were conducted using the default ResNet and the Improved BA-GWO-ResNet, as it represents the latest and most advanced variant of the proposed optimization strategy. Table 5 and Fig. 4 present the comparative performance results for this dataset.

Table 5

Results of the Military and Civilian Vehicles Classification Dataset

Model	Training Time (s)	Accuracy (%)
ResNet	135.12	93.90
Improved BA-GWO-ResNet	156.72	**94.73**

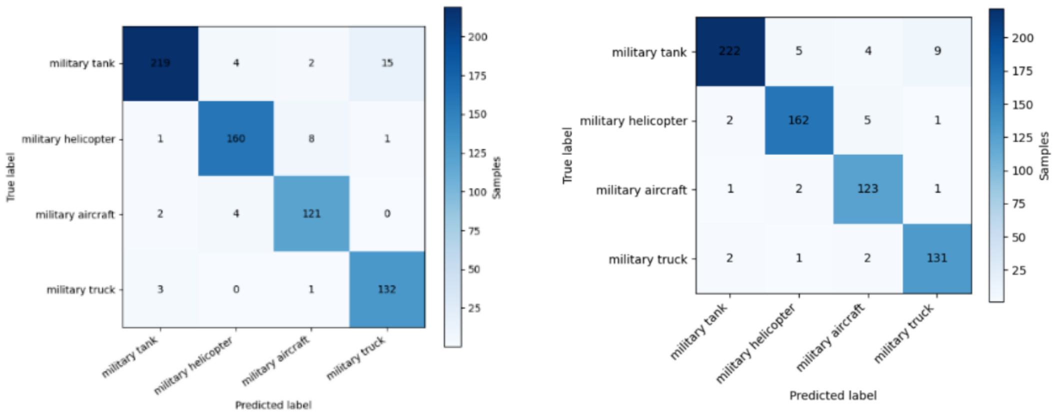

Fig. 4. Confusion matrix for the Military and Civilian Vehicles Classification Dataset using the standalone ResNet (left) and the improved BA-GWO-ResNet (right)

The optimal configurations identified by the Improved BA-GWO algorithm for the Military and Civilian Vehicles Classification dataset are listed in Table 6.

Table 6

Resulting parameters for the Military and Civilian Vehicles Classification Dataset

Model	Batch Size	Learning Rate	Activation Function	Optimizer
ResNet	128	1.0×10^{-4}	ReLU	Adam
Improved BA-GWO-ResNet	192	5.97×10^{-4}	ELU	AdamW

7. Conclusions

This paper introduced an improved BA–GWO algorithm for optimizing deep CNNs, focusing on ResNet for vehicle recognition in radar and optical

imagery. The method combines BA's adaptive local search with GWO's hierarchical global exploration, yielding strong experimental performance.
Our first contribution is an immigration strategy that periodically replaces the worst agents with new samples while always keeping the top performers, promoting diversity and preventing premature convergence.

The second contribution is the new fitness function that balances accuracy with generalization, making the approach more robust. This formulation allows the optimizer to target not only standard validation accuracy as proposed in [8], but also model generalization, particularly important for weakly balanced datasets.

Lastly, we propose a three-stage evaluation process in which candidates are first tested on reduced subsets and simpler models, then promoted to full dataset training, significantly reducing the computational cost.

Overall, the Improved BA–GWO–ResNet demonstrates a scalable and effective algorithm for deep model optimization, with potential applications even outside of the vehicle classification. Future work will extend this hybrid algorithm to more advanced architectures, such as EfficientNet [23].

R E F E R E N C E S

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