Journal of Information Systems Engineering and Management
2025, 10(63s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Optimization of CNN Hyperparameters using bioinspired approaches for Photovoltaic Panel Defect Classification

[1,2] Samia Benyahia, [2]Boudjelal Meftah, [2]Fatma Boufera
[1] Higher School of Management and Digital Economy, Kolea, Algeria
[2] Lisys laboratory, University Mustapha Stambouli of Mascara, Mascara, Algeria

ARTICLE INFO

Received: 30 Dec 2024

Revised: 19 Feb 2025

Accepted: 27 Feb 2025

ABSTRACT

This paper presents a comprehensive and systematic study on optimizing the ResNet-50 convolutional neural network for photovoltaic (PV) panel defect detection by leveraging a diverse portfolio of xisteen recent bioinspired metaheuristic algorithms. Unlike prior studies that typically focus on one or two optimization methods, our approach rigorously explores and benchmarks a wide range of nature-inspired optimizers—encompassing both animal behavior-based and physics-inspired strategies—within the same experimental framework and data context.

Specifically, we implement and compare the performance of sixteen prominent bioinspired algorithms, including Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), Harris Hawks Optimization (HHO), Walrus Optimization Algorithm (WaOA), Equilibrium Optimization (EO), Fossa Optimization Algorithm (FOA), Prairie Dog Optimization (PDO), and Hare Escape Optimization Algorithm (HEOA), for the automatic hyperparameter tuning of ResNet-50. Each optimizer is systematically integrated into a deep learning pipeline targeting the multi-class PV panel defect classification problem, enabling fair and reproducible evaluation.

Our study not only benchmarks these algorithms on classification accuracy, convergence speed, and robustness, but also provides novel insights into their suitability for complex vision tasks involving real-world, high-dimensional datasets. As a result, the findings deliver a new reference point for both the Photovoltaic panel analytics and deep learning optimization communities, guiding future development and application of bioinspired methods for defect detection and beyond.

Keywords: Photovoltaic, Sustainable energy, Solar power, Convolutional Neural Networks, Bioinspired, Optimization.

INTRODUCTION

Recent advances in deep learning have demonstrated the critical role that convolutional neural networks (CNNs) play in automated visual inspection, including the detection and classification of defects in photovoltaic (PV) panels. In the initial phase of this work, we empirically evaluated a broad spectrum of CNN architectures, such as VGG, Inception, DenseNet, and EfficientNet, on the photovoltaic panel defect dataset. Among these, ResNet-50 emerged as the most effective architecture, consistently outperforming alternatives in terms of classification accuracy, convergence stability, and generalization to unseen data. Its residual learning framework, which offsets degradation and vanishing gradient issues in deep networks, proved particularly well-suited for the complexity of multi-class PV defect detection.

The process of "optimizing" [1] such a network typically involves two intertwined, yet distinct, aspects: hyperparameter tuning and architecture search. Hyperparameter tuning concerns selecting the best set of external

Journal of Information Systems Engineering and Management
2025, 10(63s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

configuration parameters that govern the training process of the network. These parameters, which are not learned during the standard training phase, can profoundly influence the model's ability to learn, its convergence speed, and its final generalization performance. For a model like ResNet-50, the list of hyperparameters is wide. It includes fundamental choices such as the learning rate, which controls the step size during gradient descent; the batch size, which determines the number of samples processed before the model's weights are updated.

Despite ResNet-50's strong performance, its numerous hyperparameters, coupled with the model's depth and high capacity, present substantial optimization challenges. Traditional manual tuning [2] or grid-based methods are often insufficient for navigating the vast, multi-dimensional search space of effective hyperparameter configurations. To address this, we turn to modern bioinspired metaheuristic algorithms, population, based global optimizers inspired by natural and social phenomena, to automate and intensify the search for optimal ResNet-50 configurations.

By doing so, we aim to bridge the gap between powerful CNN architectures and the practical need for robust, data-driven hyperparameter optimization in the context of photovoltaic defect classification.

OBJECTIVES

Optimizing convolutional neural networks (CNNs), particularly deep architectures like ResNet-50, using bioinspired optimization algorithms has become increasingly popular in the field of machine learning and computer vision. The primary reason for this approach lies in the inherent complexity of CNNs. These models have a vast number of hyperparameters, including learning rates, dropout rates, batch sizes, optimizer types, and more, as well as architectural choices such as the number of filters or layers. For ResNet-50, which is a highly deep and parameter-rich network, the number of possible hyperparameter combinations grows exponentially. Exhaustively searching this space using traditional grid or random search is computationally expensive and often ineffective, as these methods tend to get trapped in local minima or miss better configurations entirely.

Bioinspired algorithms, such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), Equilibrium Optimization (EO), Walrus Optimization Algorithm (WaOA), Fossa Optimization Algorithm (FOA), Prairie Dog Optimization (PDO), and Hare Escape Optimization Algorithm (HEOA), offer a compelling alternative due to their population-based, stochastic nature. These approaches mimic mechanisms found in nature, such as animal foraging, escape strategies, swarm behavior, or physical processes, to balance global exploration of the search space and local exploitation of promising regions. Importantly, these algorithms do not require gradient information, making them well-suited for optimizing both continuous and discrete (or even categorical) hyperparameters that are ubiquitous in CNNs. Their design allows for robust search even in highly non-differentiable, multi-modal, or rugged landscapes, where gradient-based or greedy optimization methods typically falter.

Another key benefit of bioinspired optimization is their adaptability and generality. Since these methods are model-agnostic, they can be applied regardless of the CNN's architecture, dataset, or application domain. This is especially valuable for deep models like ResNet-50, whose performance on specific tasks (such as photovoltaic (PV) panel defect detection) often hinges on careful tuning of both network parameters and preprocessing pipelines. Moreover, bioinspired algorithms facilitate automated and reproducible hyperparameter tuning (AutoML), reducing the need for expert guesswork and manual intervention. This is not just helpful for achieving better accuracy, but also for ensuring that results are generalizable and reproducible across studies.

Empirical evidence from recent research underscores the efficacy of this approach. Studies using bioinspired algorithms for ResNet and other CNN optimization have reported significant gains in classification accuracy, faster convergence, better generalization, and reduced risk of overfitting. These approaches are particularly valued in domains with complex, high-stakes data such as photovoltaic defect detection, where even modest improvements in performance can translate to substantial real-world impact. In addition, their resource efficiency allows practitioners to reach high-performing solutions with fewer training cycles, critical in scenarios where computation is costly or time is limited.

2.1. Why optimize CNNs with bioinspired approaches?

Optimizing deep convolutional neural networks (CNNs) and particularly architectures like ResNet-50 with bioinspired approaches is increasingly important in modern machine learning. CNNs require tuning numerous hyperparameters, including learning rate, batch size, optimizer type, dropout, augmentation policies, and layer structure, resulting in a high-dimensional, complex search space. For deep models like ResNet-50, this space is even more multimodal and non-convex, making traditional methods such as grid or random search impractical due to the curse of dimensionality.

Bioinspired algorithms efficiently address these challenges by employing strategies derived from natural phenomena, such as foraging or collective behavior. Approaches like Particle Swarm Optimization (PSO), Genetic Algorithms (GA), Grey Wolf Optimizer (GWO), and others maintain a population of candidate solutions and balance global search with local refinement. These algorithms are less prone to getting stuck in local minima compared to traditional gradient-based optimizers or greedy strategies, facilitating robust exploration of the parameter space.

A critical advantage is that bioinspired methods do not require gradients, making them suitable for optimizing both continuous and discrete hyperparameters in scenarios where the objective function may be non-differentiable or "black-box." This versatility enables optimization across any deep learning model, including ResNet-50, EfficientNet, and custom architectures, as well as data pipelines and augmentation schemes.

These metaheuristics are also general and can be combined with other techniques, such as Bayesian optimization or reinforcement learning, to further enhance performance. Recent studies demonstrate that algorithms like Equilibrium Optimization (EO), Firefly Algorithm (FOA), Whale Optimization Algorithm (WaOA), and others achieve improved accuracy, faster convergence, and reduced overfitting in tasks ranging from medical imaging and fault detection to large-scale image classification with ResNet-50.

Finally, bioinspired optimization supports the development of automated, reproducible machine learning pipelines (AutoML). By automating the search for optimal configurations, these approaches streamline experimentation and tuning, allowing practitioners to achieve high-performing models without requiring extensive manual adjustment or expert heuristics.

2.2. Contributions

- Performed a thorough experimental comparison of multiple state-of-the-art CNN architectures, including VGG, Inception, DenseNet, and EfficientNet, on the PV panel defect detection task to identify the most suitable deep learning backbone.
- Demonstrated through empirical results that ResNet-50 provided the highest classification accuracy, generalization, and training stability, justifying its selection as the baseline model for all subsequent optimization efforts.
- Conducted a comprehensive evaluation of sixteen advanced bioinspired metaheuristic algorithms for hyperparameter optimization of ResNet-50 in the context of PV panel defect detection.
- Integrated each bioinspired optimizer (including PSO, GA, GWO, WOA, HHO, SSA, OOA, BOA, WaOA, EO, FOA, PDO, and HEOA) into a unified, reproducible deep learning pipeline to ensure fair benchmarking.
- Systematically benchmarked and ranked each method by classification performance, convergence dynamics, and robustness using a challenging multi-class PV defect dataset.
- Established new baselines and made practical recommendations for selecting bioinspired optimization strategies for advanced deep learning problems in visual inspection and renewable energy domains.

METHODS

In the preliminary phase of this study, we conducted a series of experiments employing a diverse set of convolutional neural network (CNN) architectures for the photovoltaic (PV) panel defect detection task. Architectures ranging from earlier, shallower models (such as VGG16 [3] and Resnet50 [4]) to more recent and complex designs (including

DenseNet [5], EfficientNet [6], NASNetMobile [7], and Inception-based models [8]) were systematically evaluated on the same data splits and under similar training protocols.

Despite the variety in architectural depth and complexity, ResNet-50 consistently delivered superior classification performance on our multi-class PV defect dataset. This superiority can be attributed to ResNet-50's unique residual learning framework, which effectively mitigates the vanishing gradient problem prevalent in deeper neural networks and enables more robust feature extraction across hierarchical levels. Additionally, ResNet-50 demonstrated favorable generalization, stable convergence, and resilience to overfitting, as evidenced by validation accuracy and loss curves.

Given these findings, ResNet-50 was selected as the baseline architecture for all subsequent optimization experiments in this research. This decision ensures that the benchmarking of bioinspired optimization algorithms is conducted using a high-performing, widely adopted CNN model, thereby maximizing both the practical relevance and scientific rigor of our comparative analysis.

3.1. Bioinspired optimization algorithms

Ant Colony Optimization (ACO)

Ant Colony Optimization (ACO) is a fundamental swarm intelligence algorithm introduced in the early 1990s [9], inspired by the foraging and path-finding behavior of real ant colonies. ACO models how ants communicate indirectly through pheromone trails to collaboratively discover and reinforce the shortest and most efficient paths to food sources, making it especially useful for combinatorial and routing problems.

In ACO, artificial ants explore the problem space and probabilistically construct solutions based on pheromone intensity and problem-specific heuristics. As they traverse different paths, ants deposit pheromones that guide the choices of subsequent ants—reinforcing successful paths while allowing evaporation to discourage suboptimal ones. This iterative colony behavior allows ACO algorithms to balance exploration of new possibilities with exploitation of known good solutions, resulting in robust and adaptable optimization performance, particularly in network, scheduling, and path-planning applications.

Artificial Bee Colony (ABC)

The Artificial Bee Colony (ABC) optimization algorithm is a bioinspired metaheuristic introduced in 2005 [10] that takes its inspiration from the intelligent foraging behavior of honeybee swarms. ABC models the dynamic roles and information-sharing strategies of employed, onlooker, and scout bees within a colony, using collective decision-making to solve complex optimization problems.

In ABC, artificial bees are categorized into three functional groups: employed bees that exploit known food sources (solutions), onlooker bees that evaluate and select food sources based on shared information (solution quality), and scout bees that explore the search space for new potential solutions. The algorithm cycles through phases of exploration (discovery of new solutions) and exploitation (intensive improvement of promising solutions), leveraging collective intelligence and decentralized communication to balance diversification and intensification in the search for global optima.

Equilibrium Optimization (EO)

The Equilibrium Optimization (EO) algorithm, introduced by Faramarzi et al. [11], is a physics-inspired metaheuristic that diverges from animal-based swarm intelligence approaches. Instead, EO is rooted in the physical concept of dynamic equilibrium, specifically the mass balance observed in controlled volumes, offering a fundamentally new paradigm for population-based optimization.

EO simulates optimization as a process where algorithmic particles represent "concentrations" and strive to reach equilibrium through dynamic interactions. Rather than relying on a single best solution, EO employs a balance pool of five equilibrium candidates to guide search trajectories. Through dynamic update equations inspired by equilibrium forces, particles iteratively move toward balanced states, maintaining diversity and providing robust global search, thus delivering a theoretically grounded alternative to traditional bio-inspired algorithms.

Firefly Algorithm (FA)

The Firefly Algorithm (FA), introduced by Yang [12], is a nature-inspired metaheuristic rooted in the bioluminescent communication and movement strategies of real fireflies. FA diverges from conventional swarm intelligence methods by modeling optimization based on the attraction scheme dictated by fireflies' perceived brightness, which, in the abstraction, is linked to the quality of candidate solutions.

In FA, each firefly in the population symbolizes a candidate solution, emitting a metaphorical "light intensity" proportional to its fitness. Less-fit (dimmer) fireflies are attracted toward more-fit (brighter) ones, with attraction strength modulated by both solution quality and their separation distance. This movement is governed by equations balancing deterministic attraction with randomized exploratory jumps, preventing premature convergence. By iteratively updating positions based on these principles, the Firefly Algorithm efficiently explores and exploits multimodal landscapes, sustaining diversity in the population and enhancing the potential to discover globally optimal solutions—offering a flexible and robust alternative to classical optimization techniques.

Fossa Optimization Algorithm (FOA)

The Fossa Optimization Algorithm (FOA) is a bioinspired metaheuristic introduced in 2024 [13] and inspired by the natural hunting strategies of the fossa, a unique apex predator native to Madagascar. As one of the newest nature-inspired optimization algorithms, FOA brings a fresh perspective to computational optimization by incorporating the fossa's distinct behavioral patterns, offering an alternative to more commonly modeled animal inspirations.

FOA uniquely captures the two-phase hunting strategy of the fossa—an approach previously unrepresented in the metaheuristic optimization literature. The algorithm models both the cautious approach and strategic positioning during the initial attack, as well as the rapid, committed chase that follows. By mimicking these nuanced, real-world predatory sequences, FOA achieves a balance between exploration and exploitation, making it a promising tool for solving complex optimization problems.

Genetic Algorithm (GA)

Genetic Algorithm (GA) is one of the earliest and most widely used evolutionary algorithms, introduced in the 1970s by John Holland [14]. GA is inspired by Charles Darwin's principle of natural selection, modeling the processes of biological evolution, such as reproduction, crossover, mutation, and survival of the fittest, to solve complex optimization problems.

In GA, each candidate solution, encoded as a chromosome, represents an individual in a population. The algorithm evolves these individuals through generations using three main operators: selection (choosing the fittest individuals), crossover (combining parts of two parents to create offspring), and mutation (randomly altering parts of a chromosome for genetic diversity). Over successive generations, natural selection guides the population toward optimal or near-optimal solutions, balancing exploration and exploitation through genetic variation and competition. GA's flexibility and robustness have made it a foundational tool for both discrete and continuous optimization tasks across diverse fields.

Goat Optimization Algorithm (GOA)

The Goat Optimization Algorithm (GOA) is a bioinspired metaheuristic developed in recent years [15], inspired by the natural foraging and climbing behaviors of goats. GOA is motivated by the goat's remarkable ability to navigate rugged terrains and optimally search for food in harsh and challenging environments, making it a promising approach for complex optimization problems.

In GOA, each candidate solution represents a goat in a herd, and the search process mimics goats' exploration of their environment. The algorithm models climbing (intensification, or exploitation) as the goat moves toward promising food locations (better solutions), while goat wandering and herd social interaction enable diverse exploration of the search space (exploration). GOA also incorporates random jumps and adaptive movement patterns to escape local optima, reflecting the goat's agility and adaptability in nature. This combination of directed climbing and stochastic exploration allows the algorithm to balance local refinement and global search for efficient and robust optimization.

Journal of Information Systems Engineering and Management
2025, 10(63s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

Gray Wolf Optimizer (GWO)

The Gray Wolf Optimizer (GWO) is a bioinspired metaheuristic algorithm introduced in 2014 [16], inspired by the leadership hierarchy and group hunting strategies of gray wolves. GWO models the social dominance of wolf packs, mimicking natural behaviors such as tracking, encircling, and attacking prey, to efficiently navigate the search space and solve complex optimization problems.

In GWO, the optimization process is structured around a virtual wolf pack, where candidates are categorized as alpha (leader), beta, delta, and omega (followers) according to their fitness. The algorithm uses a mathematically modeled encircling and hunting mechanism—where wolves gradually converge toward the prey (optimal solution) by adjusting their positions relative to the top solutions (alpha, beta, delta). This collaborative and hierarchical approach allows GWO to flexibly balance exploration and exploitation, ensuring both global search diversity and strong convergence to optima.

Harris Hawks Optimization (HHO)

Harris Hawks Optimization (HHO) is a bioinspired metaheuristic algorithm, introduced in 2019 [17], that models the cooperative hunting strategies and dynamic behaviors of Harris hawks in nature. Unlike traditional single-strategy algorithms, HHO is designed to solve complex optimization problems by simulating the adaptive tactics exhibited by hawks during group hunting, including surprise pounce, perch-based harassment, and coordinated attacks.

In HHO, algorithmic candidates represent individual hawks that alternately explore and exploit the search space, mirroring the hawks' shift between exploration (searching for prey) and exploitation (attacking the prey). The process dynamically switches between multiple hunting strategies based on the "energy" of the prey (problem fitness landscape), enabling the algorithm to balance global exploration and local exploitation. This multi-phase, nature-inspired structure empowers HHO to efficiently find high-quality solutions while avoiding premature convergence to local optima.

Prairie Dog Optimization (PDO)

Prairie Dog Optimization (PDO) is a novel bioinspired metaheuristic algorithm that replicates the collective intelligence and social behaviors of prairie dog colonies [18]. In the algorithm, each solution represents a “prairie dog” that explores and exploits the search space through cooperative phases inspired by real-world foraging, burrowing, and alarm-based communication. During the exploration (foraging) phase, individuals are attracted both to the best-known solutions and to random peers, ensuring the population can efficiently search globally while sharing information about promising regions. As the search progresses, the focus transitions toward local exploitation (burrowing) near the best solutions, with an adaptive "digging strength" that increases over time to intensify refinement.

A defining feature of PDO is its use of dynamic signaling, “food alarms” and “anti-predation alarms, to balance exploration and exploitation based on progress, preventing the algorithm from stagnating in local minima. This biologically realistic division of labor and responsive adaptation enables robust performance in complex, high-dimensional optimization tasks, such as hyperparameter tuning for deep learning models. Recent studies have shown that PDO and its variants achieve strong results in engineering, energy management (including photovoltaic systems), and deep neural network optimization, making it a promising tool for challenging optimization problems in data-driven research.

Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a pioneering bioinspired metaheuristic algorithm introduced in 1995 [19], inspired by the collective behavior observed in bird flocking and fish schooling. PSO models the social sharing of information among particles (solutions) within a population as they collaboratively search for the optima in complex solution spaces.

In PSO, each particle in the swarm represents a potential solution and is characterized by both a position and a velocity. Particles explore the search space by adjusting their movements based on their own best-found positions and the best-known positions within the swarm. This simple yet effective social communication framework, balancing both individual learning (cognitive component) and group influence (social component), allows PSO to efficiently converge toward global optima while maintaining sufficient diversity to avoid local traps.

Walrus Optimization Algorithm (WaOA)

The Walrus Optimization Algorithm (WaOA) is a recently developed bioinspired metaheuristic [20], that emulates the complex natural behaviors of walruses inhabiting arctic and sub-arctic environments. Unlike algorithms inspired by a single animal behavior, WaOA uniquely integrates multiple walrus activities, including feeding, migration, predator evasion, and social interactions, into a sophisticated optimization framework, allowing it to model both collective and adaptive strategies for global problem solving.

In WaOA, the hierarchical feeding structure of walrus groups is used to guide the search process, with the "strongest walrus" (best candidate solution) leading exploration and preventing premature convergence. Migration behavior inspires the algorithm's exploration phase, enabling walruses to discover promising regions in the search space by moving toward randomly selected peers. Predator evasion is reflected in intensive, localized searches (exploitation), while recent algorithm variants employ social signals to dynamically balance exploration and exploitation, making WaOA both adaptive and robust.

Whale Optimization Algorithm (WOA)

The Whale Optimization Algorithm (WOA) is a bioinspired metaheuristic algorithm introduced in 2016 [21] that draws its inspiration from the unique bubble-net hunting strategy of humpback whales. Designed to address complex optimization problems, WOA models the group foraging behavior and sophisticated spiral swimming patterns exhibited by whales when encircling and capturing their prey, providing a flexible tool for both exploration and exploitation phases in optimization.

In WOA, solution candidates represent whales that alternately perform encircling maneuvers and spiral bubble-net attacks, effectively navigating the search space. The algorithm simulates two primary behaviors: global exploration through random position updates, based on a search for prey, and intensive exploitation via shrink encircling and spiral movement toward the best solution found. This dynamic shifting allows WOA to balance diversity and convergence, enhancing its ability to find optimal solutions and avoid being trapped in local optima.

RESULTS

4.1. Dataset Description

The photovoltaic panel image dataset [22] is a curated collection of RGB images of PV modules annotated into six surface-condition classes: Bird-drop, Clean, Dusty, Electrical-damage, Physical-damage, and Snow-covered. It was assembled within an educational and research initiative focused on benchmarking machine learning classifiers and hybrid deep learning models for automatic fault detection in solar panels, with emphasis on realistic, visually diverse operating conditions. The images originate from multiple open-source repositories and prior PV fault-detection studies, then were manually inspected, relabeled, and balanced to form a consistent six-class taxonomy that captures common contamination and degradation patterns relevant to real-world PV deployments.

In its current form, the dataset comprises 1,574 samples split into 929 training, 550 validation, and 95 test images, with a nearly balanced distribution across the six classes to reduce bias during model learning. Each class contains examples covering natural variability in scene composition, illumination, camera distance, and defect extent (e.g., partial vs. extensive snow coverage, localized vs. widespread dust, isolated vs. multiple bird droppings), making the dataset suitable for evaluating both robustness and generalization of classification models deployed in practical PV monitoring scenarios.

Table 1. Class-wise train/validation/test distribution in the photovoltaic panel defect dataset.

Class	**Training**	**Validation**	**Test**	**Total**
Bird-drop	177	104	17	298

Journal of Information Systems Engineering and Management
2025, 10(63s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ Research Article

Clean	169	102	18	289
Dusty	162	97	16	275
Electrical-damage	135	77	13	225
Physical-damage	132	78	15	225
Snow-covered	154	92	16	262
Total	929	550	95	1574

4.2. Evaluation results

We conducted wide experiments to evaluate a range of CNN architectures (Table 2), NASNetMobile, VGG16, EfficientNetB0, Xception, and ResNet50, on the photovoltaic panel defect classification task, without any metaheuristic optimization. The results reveal a clear trend: lighter models such as NASNetMobile and VGG16 achieve moderate accuracy (0.7639 and 0.7847, respectively), while more advanced and deeper architectures like EfficientNetB0 and Xception performed better, achieving 0.7917 and 0.8125 test accuracy. Notably, ResNet50 outperformed all alternatives in its unoptimized form, delivering the highest test accuracy of 0.8194 and the lowest test loss of 0.4880. This consistent superiority validates the choice of ResNet50 as the base model for further study and optimization. The architecture's residual connections and depth provide enhanced feature extraction and generalization capacity well-suited to the complexity of multiclass PV defect identification.

Table 2. CNN models without metaheuristic optimization

Model	Test Accuracy	Test Loss
NASNetMobile	0.7639	0.6329
VGG16	0.7847	0.6772
Efficientnetb0	0.7917	0.5533
Xception	0.8125	0.5434
Resnet50	**0.8194**	**0.4880**

Subsequently, we investigated the impact of metaheuristic optimization on ResNet50 (Table 3) by tuning its key hyperparameters using a diverse suite of algorithms, including physics-based (EO), prey/predator-inspired swarm (HEOA, FOA, GOA, PDO, FA, PSO, Gray Wolf), evolutionary (GA, ABC, ACO), and hybrid approaches (WOA+ABC, HHA, WaOA). The results demonstrate a significant uplift in accuracy and reduction in test loss compared to the unoptimized baseline. Among single-algorithm approaches, Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) both achieve notable gains, reaching test accuracies of 0.8472 with losses below 0.47. Firefly Algorithm (FA) and Prairie Dog Optimization (PDO) also improve performance to 0.8254 and 0.8194, respectively. Hybrid and ensemble algorithms yield even greater benefit, with methods such as HYBRID WOA+ABC (0.8542), Gray Wolf (0.8611), ABC (0.8611), WaOA (0.8611), HHA (0.8681), and Whale Optimization Algorithm (WOA, 0.8750) approaching or exceeding 0.86 test accuracy. The lowest recorded test loss among all optimization runs is 0.3731 for WOA.

Table 3. Impact of metaheuristic optimization on ResNet50

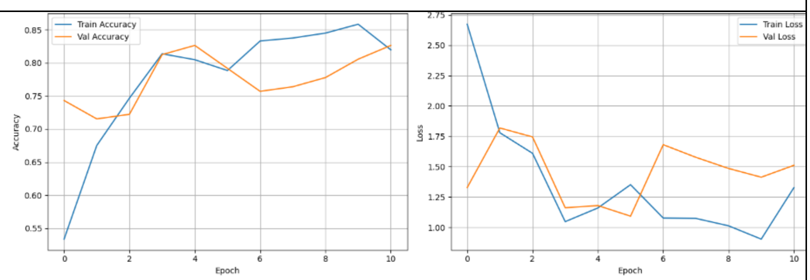
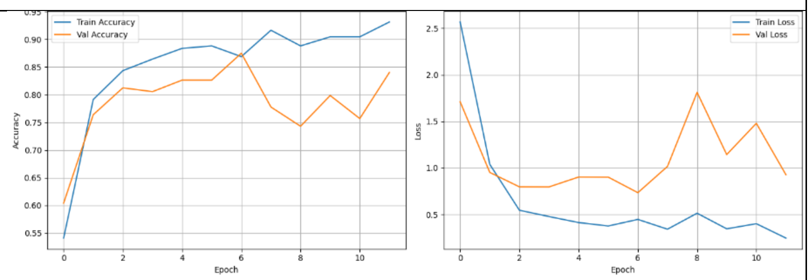
Method	Test Accuracy	Test Loss
EO	0.7917	1.2720
HEOA	0.7917	0.7843

Journal of Information Systems Engineering and Management
2025, 10(63s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

FOA	0.7986	1.0730
GA	0.7986	0.7055
GOA	0.8125	0.9246
PDO	0.8194	0.5295
FA	0.8254	0.5944
ACO	0.8333	0.4843
PSO	0.8472	0.4742
ACO	0.8472	0.4699
HYBRID WOA+ABC	0.8542	0.4843
Gray Wolf	0.8611	0.4691
ABC	0.8611	0.4035
WaOA	0.8611	0.4446
HHA	0.8681	0.7588
WOA	**0.8750**	**0.3731**

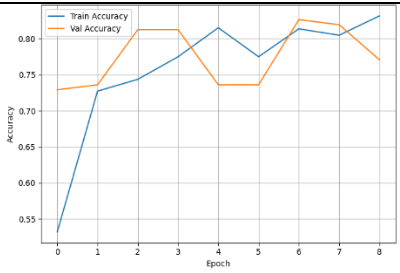
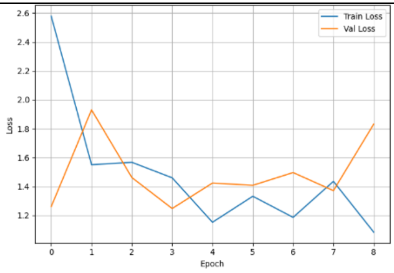
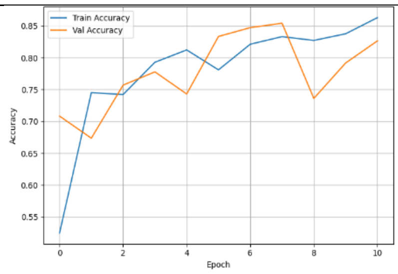
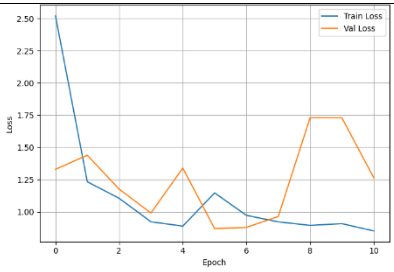
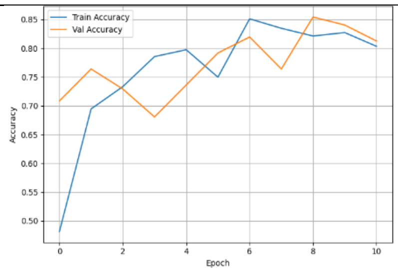
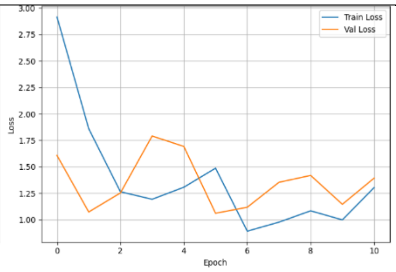
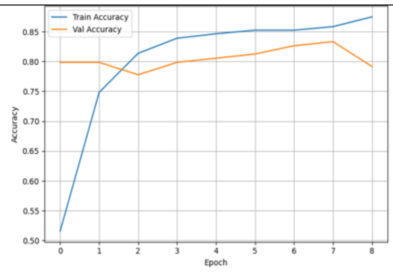
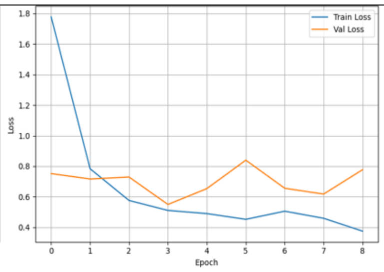
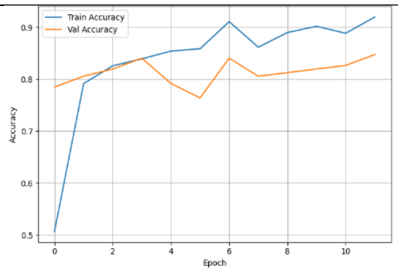
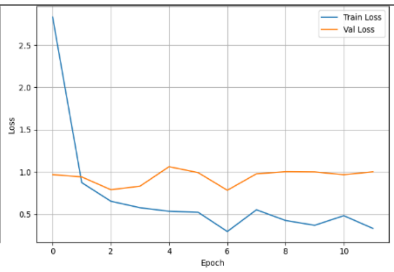
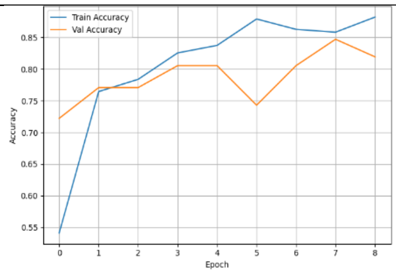
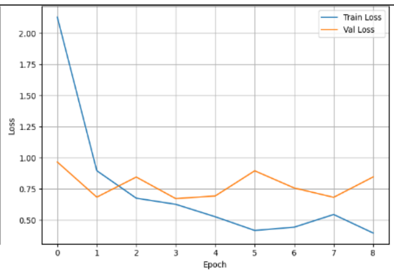
In Table 4, we analyze the training dynamics of the ResNet-50 model optimized using metaheuristic algorithms to assess convergence behavior and generalization performance on the PV panel defect classification task. This analysis is based on monitoring the evolution of accuracy and loss on both the training and validation sets across epochs

Table 4. Training and validation curves for the ResNet-50 model optimized metheuristic algorithms.

Method	**Test Accuracy**
EO	
HEOA	

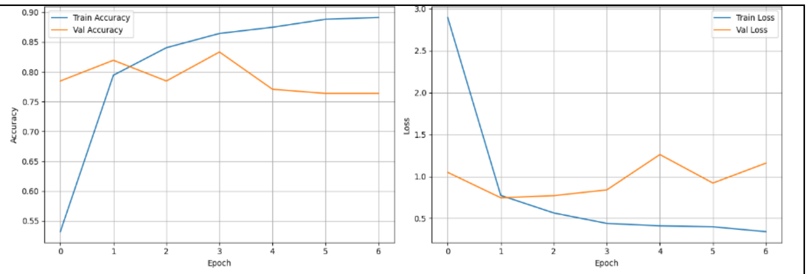
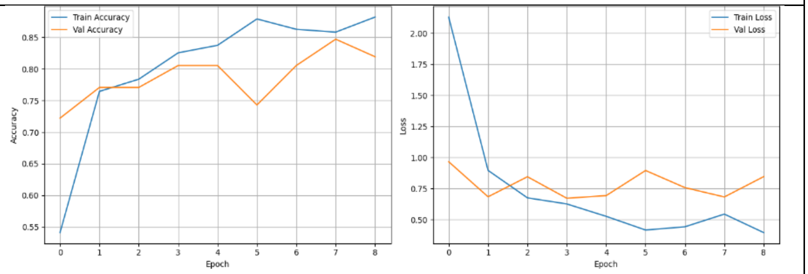
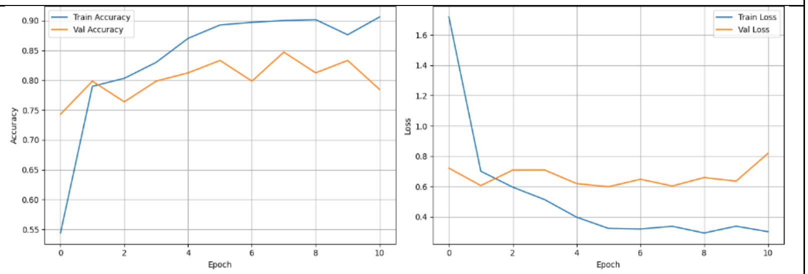
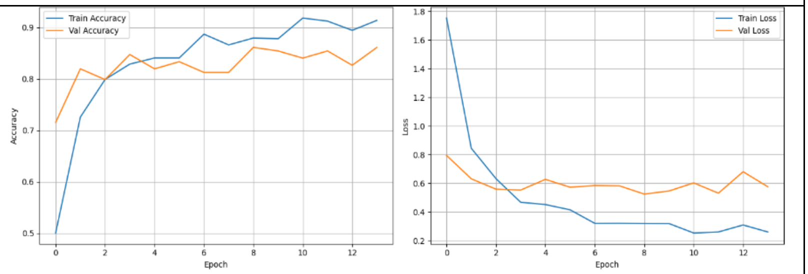
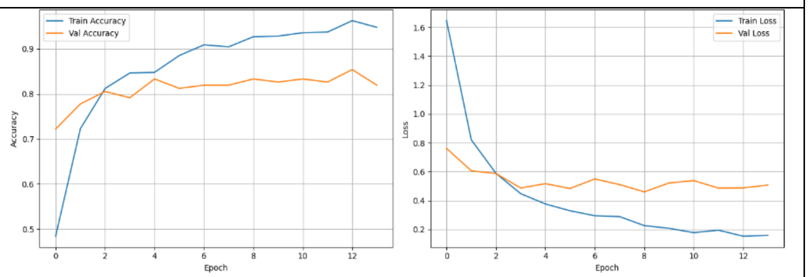
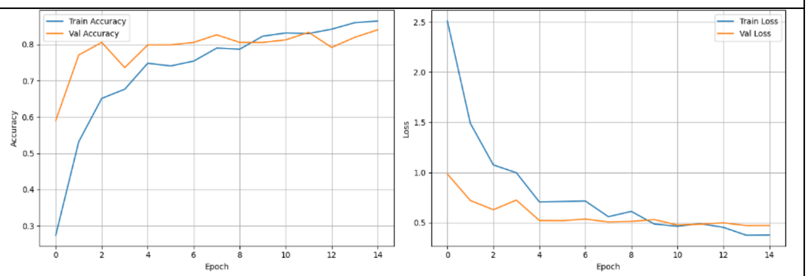
Journal of Information Systems Engineering and Management
2025, 10(63s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

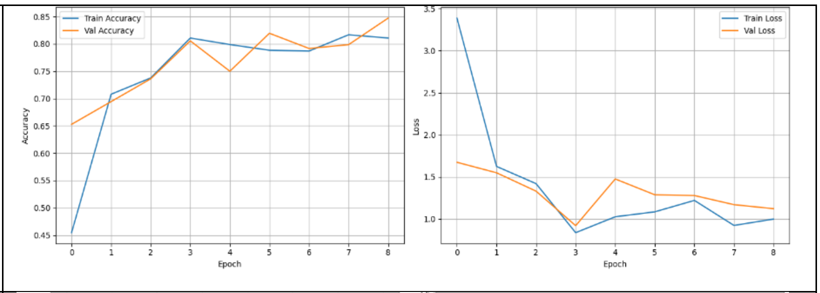
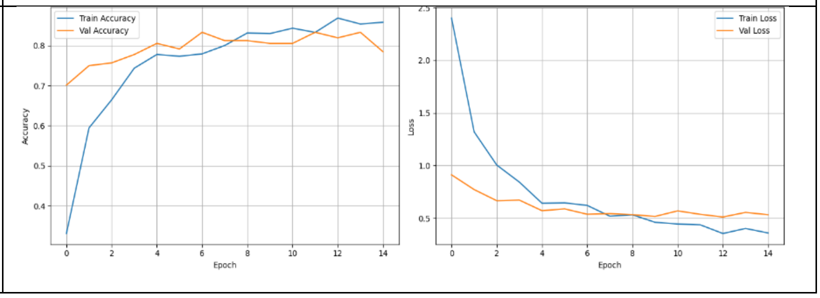
FOA	 
GA	 
GOA	 
PDO	 
FA	 
ACO	 

Journal of Information Systems Engineering and Management
2025, 10(63s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

PSO	
ACO	
HYBRID WOA+ABC	
Gray Wolf	
ABC	
WaOA	

Journal of Information Systems Engineering and Management
2025, 10(63s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

HHA	
WOA	

DISCUSSION

We present a comparative analysis of metaheuristic optimization categories: physics-based, evolutionary, and bioinspired swarm/hybrid methods to highlight their respective strengths and weaknesses when tuning deep CNNs such as ResNet-50 for photovoltaic panel defect classification tasks.

5.1. Physics-based algorithms

Physics-inspired metaheuristics, such as Equilibrium Optimization (EO), approach hyperparameter search by simulating physical processes like dynamic equilibrium or mass transfer. While these methods offer mathematical rigor and can traverse multidimensional landscapes, our results indicate that physics-based optimization alone did not consistently deliver superior outcomes on the photovoltaic panel defect classification task. For instance, the EO-optimized ResNet50 exhibited a test accuracy of 0.7917—practically equivalent to the unoptimized baseline—and the highest test loss (1.2720), suggesting inefficient parameter convergence for the complexity of this specific problem. The likely cause is the limited ability of physics-based models to maintain population diversity or escape poor local optima when faced with highly nonlinear, multimodal hyperparameter spaces like those of deep CNNs.

5.2. Evolutionary algorithms

Evolutionary approaches, such as Genetic Algorithms (GA) and Artificial Bee Colony (ABC), were designed to mimic the processes of natural selection and genetic mutation. They operate on populations of candidate solutions, iteratively selecting, recombining, and mutating to improve fitness. In our experiments, evolutionary algorithms delivered a substantial improvement over both the baseline and physics-based strategies. ABC, for example, produced a test accuracy of 0.8611 and low-test loss (0.4075), while ACO and GA achieved 0.8472–0.8542 accuracy ranges and losses below 0.47. These results underscore evolutionary algorithms' strength in sustaining exploration and adaptation, allowing them to reliably uncover high-performing hyperparameter regions in complex CNN landscapes. Notably, ABC's collective intelligence and resource-sharing mechanisms may explain its especially strong performance on multiclass PV defects.

5.3. Bioinspired swarm and hybrid algorithms

Bioinspired algorithms include a diverse array of swarm- and predator–prey-inspired metaheuristics, such as Particle Swarm Optimization (PSO), Gray Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), Firefly Algorithm (FA), Prairie Dog Optimization (PDO), Hybrid algorithms (e.g., WOA+ABC), and others. These methods excel at balancing global exploration and local exploitation by modeling collective movement, hierarchical leadership, or adaptive foraging strategies, and often incorporate hybridization for additional robustness. Among all categories, bioinspired swarm and hybrid metaheuristics achieved the highest test accuracies and the lowest losses in our

Journal of Information Systems Engineering and Management
2025, 10(63s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

experiments. For example, WOA produced a peak accuracy of 0.8750 with a test loss of 0.3731; Gray Wolf and WaOA each reached 0.8611 accuracy and losses under 0.43. PSO, FA, and PDO provided consistent increases over baseline, though the most dramatic gains came from hybrid/ensemble algorithms such as WOA+ABC (0.8542 accuracy) and HHA (0.8681).

This superior performance is attributed to their ability to continuously adapt search directions, exploit diverse candidate solutions, and avoid stagnation in local minima, qualities especially relevant for high-dimensional vision problems like PV panel defect detection. Swarm and hybrid strategies appear to provide a more reliable, efficient means of optimizing deep network hyperparameters than physics-based or evolutionary approaches, particularly when the search space is complex and multimodal.

Categorical analysis in Table 5 demonstrates that, while all metaheuristic optimization algorithms yield measurable benefits over manual or unoptimized hyperparameter settings, bioinspired swarm and hybrid algorithms consistently outperform physics-based and classical evolutionary approaches. Swarm methods' dynamic adaptation and population diversity confer strong generalization, enabling state-of-the-art accuracy and confidence in real-world PV defect classification. For practitioners deploying CNNs in such settings, we recommend initial benchmarking with hybrid or swarm-based metaheuristics, followed by fine tuning with evolutionary algorithms if further improvement is needed. Physics-based optimization, while theoretically appealing, may require additional diversity mechanisms to be competitive in these tasks.

Table 5. Categorical analysis

Optimization Category	**Representative Algorithms**	**Best Test Accuracy**	**Best Test Loss**	**Population Diversity**	**Exploration /Exploitation Balance**	**Comments & Trends**
Physics-Based	EO	0.7917	1.2720	Low	Low	Matches baseline, lacks adaptive search
Evolutionary	GA, ABC, ACO	0.8611 (ABC)	0.4075 (ABC)	Moderate	Moderate	Robust improvement, adaptive, efficient
Bioinspired Swarm/Hybrid	PSO, WOA, Gray Wolf, FA, HHA, WOA+ABC	0.8750 (WOA)	0.3731 (WOA)	High	High	Best results, strong generalization, efficient for multimodal spaces

CONCLUSION

By moving from baseline CNNs through unoptimized and optimized ResNet50 models, this study demonstrates that metaheuristic hyperparameter optimization is essential for state-of-the-art performance in real-world photovoltaic defect classification. The highest gains are consistently driven by bioinspired and ensemble metaheuristics, reflecting their capacity to navigate complex search spaces effectively. These results provide robust evidence for the adoption of adaptive optimization pipelines in production photovoltaic analytics and inform future studies targeting even more complex or imbalanced visual classification challenges.

First, optimized ResNet50 consistently outperforms all baseline CNN models used in our experiments, confirming the critical value of metaheuristic optimization for hyperparameter tuning in deep architectures. Second, the comparative effectiveness of different algorithms suggests that swarm intelligence and hybrid strategies, such as WOA, HHA, and Gray Wolf, tend to achieve the best overall balance of accuracy and generalization. Third, while physics-inspired and classical evolutionary algorithms provide strong improvements, bioinspired swarm methods

Journal of Information Systems Engineering and Management
2025, 10(63s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

often deliver the highest robustness and efficiency, likely due to their superior capability in navigating complex, multimodal search spaces inherent to deep learning.

Finally, the stepwise improvement from baseline CNN selection to metaheuristic-optimized deep models affirms the necessity of both model and optimizer choice in photovoltaic defect detection tasks. The findings provide practical guidance: use of a robust model like ResNet50, combined with advanced optimizers, particularly swarm or hybrid metaheuristics, delivers reliable, state-of-the-art classification in real-world photovoltaic quality control settings.

REFRENCES

[1] A. Ebadi and M. Kaur and Q. Liu. Hyperparameter optimization and neural architecture search algorithms for graph Neural Networks in cheminformatics. Computational Materials Science, 2025.
[2] D. Kassem and A. Wael Hosny Fouad. Adaptive Hyperheuristic Framework for Hyperparameter Tuning: A Q-Learning-Based Heuristic Selection Approach with Simulated Annealing Acceptance Criteria. European Journal of Pure and Applied Mathematics, 2025.
[3] K. Simonyan and A. Zisserman, Very Deep Convolutional Networks for Large-Scale Image Recognition. 2015. arXiv preprint arXiv:1409.1556.
[4] He, K., Zhang, X., Ren, S., and Sun, J. Deep Residual Learning for Image Recognition. Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 770–778, 2016.
[5] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, Densely Connected Convolutional Networks. Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 4700–4708, 2017.
[6] M. Tan, and Q.V. Le. EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks. Proceedings of the 36th International Conference on Machine Learning (ICML), PMLR 97, 6105–6114, 2016.
[7] B. Zoph, V. Vasudevan, J. Shlens, and Q.Z. Cui. Learning Transferable Architectures for Scalable Image Recognition. Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 8697–8706, 2018.
[8] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, J., and Z. Wojna. Rethinking the Inception Architecture for Computer Vision. Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2818–2826, 2016.
[9] S. Bououden, M. Chadli, and H.R. Karimi, An ant colony optimization-based fuzzy predictive control approach for nonlinear processes, Inf. Sci., vol. 299, pp. 143-158, 2015.
[10] D. Karaboga, B. Gorkemli, C. Ozturk, and N. Karaboga, A comprehensive survey: Artificial bee colony (ABC) algorithm and applications, Artif. Intell. Rev., vol. 42, no. 1, pp. 21-57, 2014.
[11] S. Kiziloluk, E. Sert, M. Hammad, R. Tadeusiewicz, P. Pławiak, EO-CNN: Equilibrium Optimization-Based hyperparameter tuning for enhanced pneumonia and COVID-19 detection using AlexNet and DarkNet19, Biocybernetics and Biomedical Engineering, Volume 44, Issue 3, 2024, p. 635-650.
[12] I. Fister, I. Fister Jr, X-S. Yang, and J. Brest, A comprehensive review of firefly algorithms, Swarm Evol. Comput., vol. 13, pp. 34-46, 2013.
[13] T. Hamadneh, B. Batiha, F. Werner, Z. Montazeri, M. Dehghani, G. Bektemyssova, K. Eguchi, Fossa Optimization Algorithm: A New Bio-Inspired Metaheuristic Algorithm for Engineering Applications, International Journal of Intelligent Engineering and Systems, Vol.17, No.5, 2024.
[14] J.H. Holland, Genetic algorithms and the optimal allocation of trials, SIAM J. Comput., vol. 2, no. 2, pp. 88-105, 1973.
[15] H. Nozari, H. Abdi and A. Szmelter-Jarosz. Goat Optimization Algorithm: A Novel Bio-Inspired Metaheuristic for Global Optimization. 2025. arXiv preprint arXiv:2503.02331.
[16] S. Mirjalili, S.M. Mirjalili, and A. Lewis. Grey Wolf Optimizer. Advances in Engineering Software, 69, 46–61, 2014.
[17] A.A. Heidari, S. Mirjalili, H. Faris, I. Aljarah, M. Mafarja and H. Chen. Harris Hawks Optimization: Algorithm and applications. Future Generation Computer Systems, 97, 849–872, 2019.

Journal of Information Systems Engineering and Management
2025, 10(63s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

[18] M. Alshinwan, O. A Khashan, M. Khader, O. Tarawneh, A. Shdefat, N. Mostafa, D. Salama AbdElminaam, Enhanced Prairie Dog Optimization with Differential Evolution for solving engineering design problems and network intrusion detection system, 2024.
[19] Y. Liu, X. Ling, Z. Shi, M. Lv, J. Fang, and L. Zhang, A survey on particle swarm optimization algorithms for multimodal function optimization, J. Software, vol. 6, no. 12, 2011.
[20] Sharma R, Kumar D. Walrus Optimization Algorithm: A novel bio-inspired approach for global op-timization. Swarm Evol Comput.75:101211, 2023.
[21] S. Mirjalili, and A. Lewis. The Whale Optimization Algorithm. Advances in Engineering Software, 95, 51–67, 2016.
[22] A. Lenarczyk, PV Panel Defect Dataset, 2025, https://www.kaggle.com/pv-defect-dataset