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Explainable fault diagnosis using discrete grey wolf optimization algorithm for photovoltaic system

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ABSTRACT

The present article introduces the discrete grey wolf optimization algorithm (DGWOA), a novel variant of the grey wolf optimizer (GWO). DGWOA integrates discrete optimization techniques with explainable artificial intelligence (XAI) methodologies. This approach aims to overcome limitations associated with traditional fault diagnosis methods, such as limited accuracy in identifying complex patterns and low interpretability. Furthermore, it mitigates early convergence problems commonly encountered in optimization algorithms and enhances adaptability to discrete classification challenges. The DGWOA algorithm is designed to generate interpretable classification rules for fault detection through a stochastic search strategy. The explainability provided by the model not only enhances decision-making transparency but also improves diagnostic efficiency and predictive accuracy. The proposed algorithm was evaluated using a photovoltaic system dataset and benchmarked against established rule-based classifiers. DGWOA consistently achieved a classification accuracy of 99.48% and a precision of 100%, demonstrating its effectiveness in enhancing fault detection. Moreover, the interpretability of the generated classification rules contributes to the generation of outcomes that are both actionable and comprehensible to decision-makers.

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1. INTRODUCTION

The rapid advancement of contemporary technology has positioned solar energy as a leader in global renewable power generation. [1], [2]. This worldwide growth is mostly ascribed to the essential function of solar energy in reducing pollution and lessening the detrimental impacts of environmental degradation. [3], as well as the continuous depletion of fossil fuel reserves, which has amplified the global demand for sustainable alternatives. Among the most promising technologies, photovoltaic (PV) systems stand out due to their environmental benefits, sustainability, and safety [4]. However, several studies [5], [6] have reported that these systems are susceptible to sudden faults that may result in significant energy losses and reduced component lifespan. This underscores the need for precise and rapid defect identification to ensure optimal performance and minimize maintenance expenses.

Numerous conventional techniques have been used to overcome these difficulties, such as statistical techniques [7] and classical machine learning algorithms [8]. Nevertheless, their performance tends to decline as system complexity and scale increase. Consequently, metaheuristic algorithms have garnered substantial attention due to their capability to enhance fault detection and parameter extraction using nature-inspired optimization strategies [9], [10]. For instance, Juan *et al.* [11] proposed a hybrid simulation combining metaheuristic algorithms to tackle complex optimization problems. At the same time, the fitness-distance balance-based stochastic fractal search (FDB-SFS) approach [12] demonstrated superior performance in extracting parameters of photovoltaic adaptive guided differential evolution algorithm (AGDE) models. Furthermore, algorithms such as the artificial hummingbird algorithm (AHA) [13] and modified social network search algorithm combined with the secant method (MSNS-SEC) [14], along with several variants of particle swarm optimization (PSO), have demonstrated remarkable optimization capabilities and results [15].

Additional developments include an ANFIS model integrated with the PSO algorithm, which effectively reduced total harmonic distortion (THD) in a UPS system powered by $LiFePO_4$ batteries [16]. Moreover, the tree seed optimization (TSO) technique demonstrates a notable superiority over multiple methods for result accuracy and convergence speed. [17]. Hybrid models, such as dung beetle optimization algorithm combined with Fick's law of diffusion algorithm dung beetle optimization algorithm combined with Fick's law of diffusion algorithm (DBFLA) [18], QPSOL [19], and whale optimization algorithm- artificial neural network (WOA-ANN) [20], have also achieved outstanding performance in fault classification and improving diagnostic accuracy.

In this context, the grey wolf optimizer (GWO) has emerged as one of the most efficient metaheuristic methods, both in its original form and through its various modified and hybrid variants, owing to its high performance in photovoltaic system applications; these advancements have contributed to faster dynamic response, reduced energy losses, and improved voltage stability under variable operating conditions [21]–[31]. Despite the proven efficiency of various GWO variants in numerous optimization tasks, their black-box nature limits interpretability and traceability, key requirements in sensitive fields such as photovoltaic systems. To overcome this limitation, the diversified grey wolf optimizer algorithm (DGWOA) has been introduced. By integrating cooperative search strategies with explainable AI (XAI) techniques, DGWOA enhances transparency while preserving high classification accuracy. Its hybrid framework enables the generation of explicit decision rules and incorporates a dynamic control mechanism to balance exploration and exploitation, ensuring adaptability and improved convergence.

The next parts of this document are organized as outlined. Methodology outlines the proposed technique, including the classification task, the error categories considered, and the datasets utilized. The experimental results section presents a comprehensive evaluation and comparative analysis with existing models. Finally, the research ends with a synthesis of the main results, highlighting the model's improved robustness, reliability, and suitability for real world PV system applications.

2. METHOD

2.1. Discrete grey wolf optimization (DGWOA)

This research study presents the DGWOA, a novel adaptation of the original technique molded GWO by the social hierarchy and hunting behaviors of wolves. Integrated with explainable artificial intelligence techniques, DGWOA facilitates the generation of interpretable classification rules, thereby enhancing the transparency and reliability of decision-making. Figure 1 shows the structure of the DGWOA-based system for diagnosing photovoltaic (PV) faults. This system enhances overall efficiency and accelerates solution convergence when dealing with complex optimization problems. Figure 2. The overall structure of the proposed method is based on DGWOA.

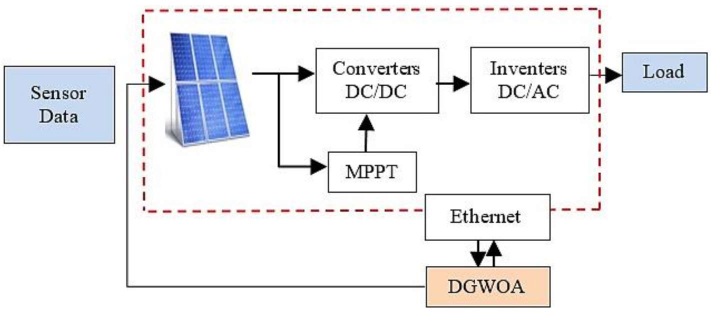

Figure 1. Structure of the DGWOA-based system for diagnosing PV faults

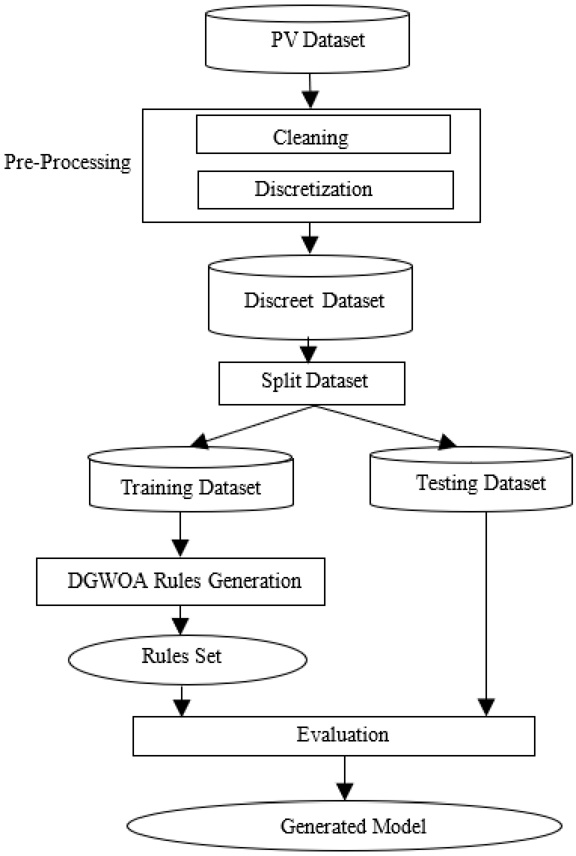

Figure 2. The proposed method DGWOA

Algorithm 1 represents the practical implementation of a hybrid framework that combines the GWO algorithm with explainable AI (XAI) techniques. It demonstrates how this integration enables accurate fault diagnosis in photovoltaic systems while ensuring the level of interpretability required for real world operating environments.

Algorithm 1. DGWOA – a discrete grey wolf optimizer for rule-based classification
Input parameters:
  D_train: Training dataset used for rule induction
  D_test: Testing dataset used for model evaluation
  W: Total number of search agents (wolves)
  Max_iter: Maximum number of optimization iterations per rule
  Min_instance: Minimum number of uncovered training instances to extract a rule
Output:
  A set of classification rules for each target class
  Performance metrics: Accuracy, Precision, TP, FP, TN, FN
Methodological framework:
A. Initialization phase
  Initialize the algorithm parameters: W, Max_iter, Min_instance
  Start execution timer
  Define empty rulesets: Ruleset_C1, Ruleset_C2, ..., Ruleset_Cn
B. Rule extraction phase
For each class Ci ∈ {C1, C2, ..., Cn}:
  Partition D_train into:
    D_pos: Instances of class Ci
    D_neg: Instances not belonging to Ci
While |D_pos| > Min_instance:
  Randomly initialize W wolves (candidate rules)

For each iteration t = 1 to Max_iter:
Evaluate the fitness of each wolf using the defined fitness functions (Equations 1 and 2)
Select the top three wolves as Alpha (best), Beta (second-best), and Gamma (third-best)
Update positions of the remaining wolves using the DGWOA strategy
After Max_iter, set the Alpha wolf's vector as a new rule
Apply the new rule on the training set D_train
Remove covered instances from D_train
Add the new rule to Ruleset_Ci

C. Testing phase
Apply the extracted ruleset on the test dataset D_test
For each class Ci:
Compute confusion matrix: TP, FP, TN, FN
Calculate performance metrics: Accuracy, Precision

D. Aggregation and reporting
Combine results for all classes
Report final classification performance metrics and runtime

2.2. The dataset

This study utilized a dataset available on the Kaggle platform, which represents operational measurements of a photovoltaic system collected from a simulated 250 kW solar farm, focusing on detecting multiple types of faults (F1, F2, and F3) alongside the normal operating state (F0). It includes sampled measurements of environmental factors, including temperature, sun irradiance, and fault resistance, with essential electrical variables, including current, voltage, and power [32].

2.3. Rule generation and fitness evaluation

The proposed prediction and diagnosis approach is based on extracting classification rules that define system operational states through structured logical conditions, enabling their categorization into predefined classes. The rule generation process is driven by a relevance function grounded in the support metric [33], [34] as in (1); which evaluates each rule based on the total number of instances (TI), correctly covered cases (ICC), and incorrectly covered cases (INCC) as in (2). Figure 3 illustrates the methodological framework an iterative refinement cycle to improve classification accuracy and ensure diagnostic reliability.

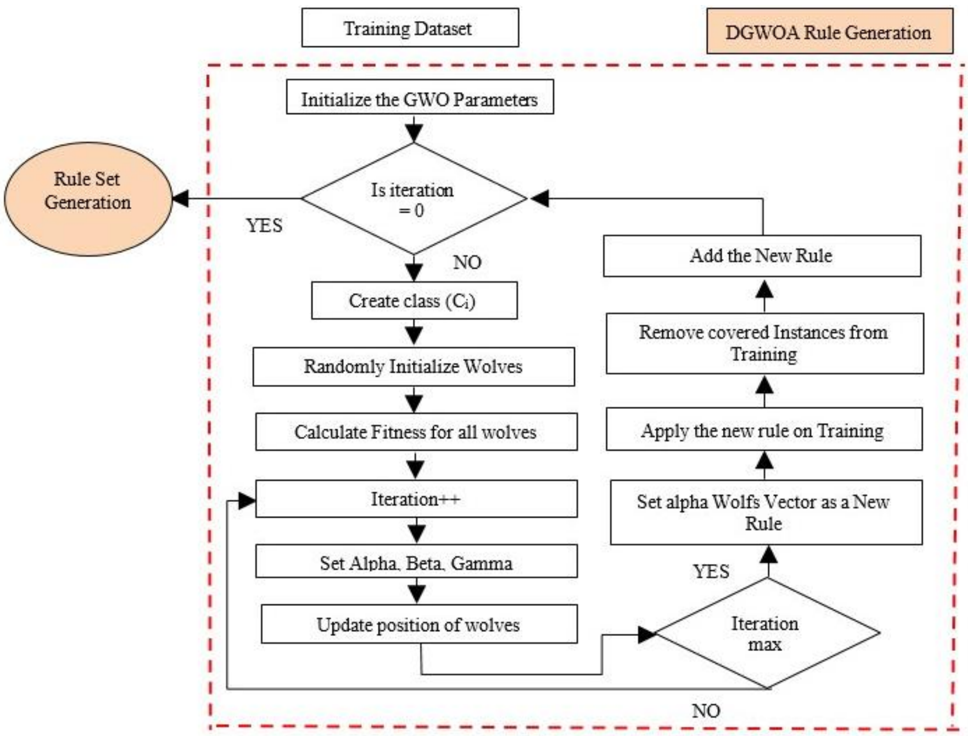

Figure 3. Flowchart of the proposed rule-based fault diagnosis approach

$$Support\ metric = \frac{ICC}{TI} \tag{1}$$

$$Fitness\ Function = \frac{TI}{(TI-ICC)*(TI+INCC\ )} \tag{2}$$

Formula for classification rules:

$$\underbrace{\text{If } \overbrace{\text{Attribute X}}^{\text{Attribute value}} \text{ Equals Value 1, } \overbrace{\text{Attribute Y}}^{\text{Attribute label}} \text{ equals Value 2, AND } \overbrace{\text{Attribute Z equals Value 3}}^{\text{Term}}}_{\text{Initial Conditions}} \text{ Then } \underbrace{\text{the class is C}}_{\text{Outcome}}$$

3. EXPERIMENTAL

3.1. DGWOA evaluation

The DGWOA algorithm was executed multiple times on photovoltaic (PV) system data by varying the number of wolves and iterations, with automatically generated seed values in each run. As presented in Table 1, the best performance was achieved with 110 wolves and 10 iterations, yielding a classification accuracy of 0.99 and a precision of 1.00 within an execution time of less than 6 minutes. Increasing the number of wolves beyond this configuration yielded no further improvements and resulted in a slight decline in efficiency. These findings highlight the importance of identifying an optimal configuration that strikes a balance among classification accuracy, computational expense, and search efficacy.

Table 1. DGWOA performance under varying numbers of wolves and iterations

Number of wolves	Number of iterations	Accuracy	Precision
20	5	0.81	0.75
50	8	0.81	0.75
110	10	0.99	1.00
120	15	0.76	0.62
135	25	0.81	0.75
180	30	0.78	0.65
200	50	0.82	0.70

3.2. Rule set generation

Table 2 presents the classification rules generated by the DGWOA algorithm, yielding four distinct rules: one for the normal condition (F0–Class 1) and three for fault scenarios (F1, F2, and F3–Classes 2, 3, and 4). While some rules achieved high classification accuracy and substantial data coverage, reaching benchmark level performance, others showed reduced accuracy and lower coverage, indicating variability in generalization. Rule coverage ranged from 16% to 34% (94 to 198 instances), highlighting areas for potential refinement to improve completeness and reliability. Table 3 presents the true-positives (TP), false-positives (FP), true-negatives (TN), and false-negatives (FN) values per class, and Table 4 provides a confusion matrix-based performance analysis, enabling a detailed evaluation across all fault categories.

Table 2. The resulting rules

Rule #	Generated rules	Class	Number of terms	Number of instances correctly covered	Number of instances not correctly covered	Rule's accuracy
01	If range1 in range (0.00193) - (0.1069) and range3 in range > (0) then Normal mode (F0)	Class1	2	94/100	0	16 %
02	If range1 in range (0.1069) - (5.3141) and range3 in range > (0) then Default1 (F1)	Class2	2	144/146	1	24%
03	If range3 in range (-4.25) - (-0.0662) and range4 in range < (0) then Default2 (F2)	Class3	2	143/144	0	24%
04	If range4 in range > (0.0621) then Default3 (F3)	Class4	1	198/198	0	34%
Evaluate	**Correctly classified instances = 96 out of 97.96** **Model accuracy= 0.99** **Model precision= 1.0**					

Table 3. Model performance

Class	TP	FP	TN	FN	Accuracy	Precision
Class C1	25	0	73	0	1.0	1.00
Class C2	23	0	75	0	1.0	1.00
Class C3	23	0	73	2	0.98	1.00
Class C4	25	0	73	0	1.0	1.00

3.3. Evaluation of model performance using receiver operating characteristic curves and area under the curve

Figure 4 presents the results of the receiver operating characteristic (ROC) curve and area under the curve (AUC) metrics, indicating that the model effectively distinguishes between positive and negative instances across all four classes (C1, C2, C3, and C4). The precision and AUC scores for C1, C2, and C4 are nearly perfect, approaching 1.00, while those for C3 are 0.98 and 0.96, respectively. These values substantially exceed the random classification threshold (AUC = 0.5), as in Figure 5. Analysis of classifier performance using confusion matrix illustrated in the figure. Overall, the results confirm the model's strong classification performance, its robust discriminative power across multiple categories, and its high predictive accuracy, supporting its applicability in complex classification tasks.

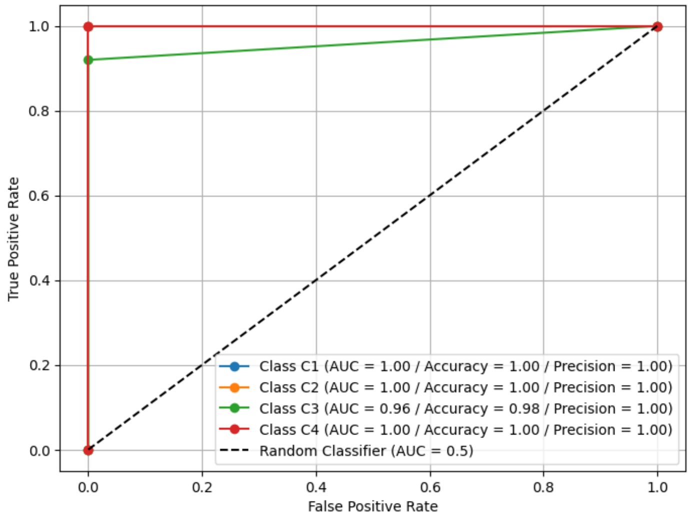

Figure 4. Multi-class ROC curves with AUC, accuracy, and precision

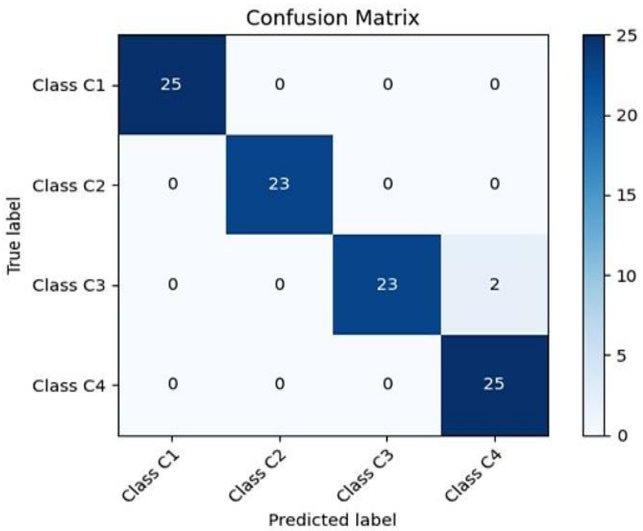

Figure 5. Analysis of classifier performance using confusion matrix

3.4. Assessment of DGWOA in comparison with conventional techniques

The proposed DGWOA algorithm was evaluated through two comparative experiments on a benchmark dataset one using traditional classifiers [33], the other using WEKA-based models. The results confirmed its superior performance, with 99.48% accuracy, 0.99 AUC, 0.9896 F1-score, perfect precision, and 0.9796 recall. DGWOA also generated interpretable "if–then" rules, aligning with explainable AI (XAI). In contrast, ensemble models such as AdaBoost and random forest demonstrated high accuracy but lacked interpretability. Conventional and low-performing models (e.g., CN2, naive Bayes, and ZenoR) underperformed or failed to generate rules as summarized in Table 4 and illustrated in Figure 6. Overall, DGWOA demonstrates a strong balance between predictive accuracy and transparency, making it suitable for high-stakes decision-making.

Table 4. Comparative analysis with other classifiers

Model	CA (%)	F1-Score (%)	Precission (%)	Recall (%)	Specificity (%)	Generation the Rules (If-Then)
DGWOA	**99.48**	**98.96**	**100**	**97.96**	**100**	**YES**
Adaboost [33]	95	94.9	95.8	95	98.3	NO
Random forest [33]	81	80.6	83.4	81	93.7	NO
Lasso-regression [33]	76	75.3	79.9	76	92	NO
Ridge-regression [33]	71	69.4	73.3	71	90.3	NO
Naives Bayes [33]	60	58.9	58.4	60	86.7	NO
CN2 rule induction [33]	50	48.5	51.8	50	83.3	YES
Zenor (WEKA Platform)	25.5	10.4	6.5	25.5	74.5	NO
Oner (WEKA Platform)	67.6	42.9	38.7	51.0	84.1	NO
Decision table (WEKA platform)	0.735	66.1	85.6	73.5	90.9	YES

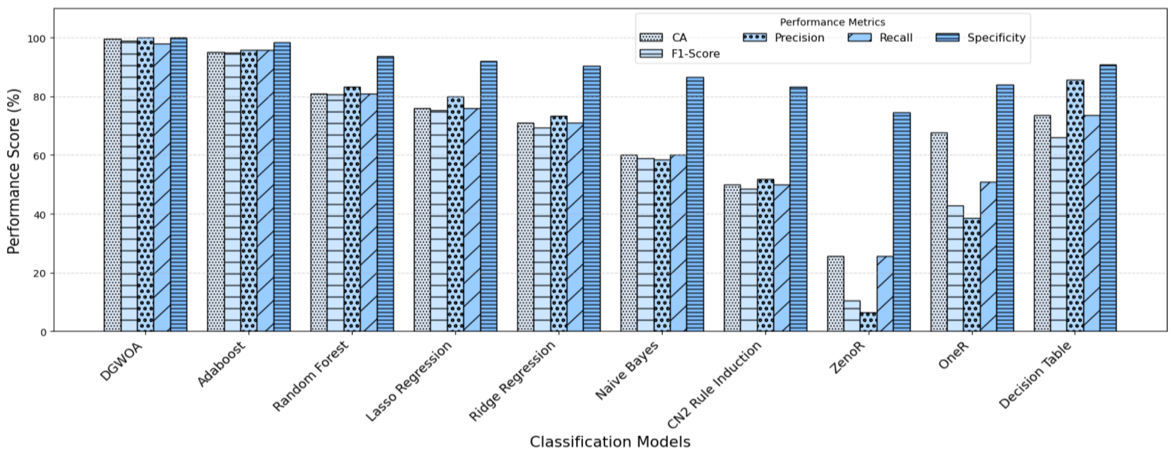

Figure 6. Comparing algorithms using different criteria

3.5. Statistical stability of DGWOA based on max fitness performance

To evaluate the reliability of the DGWOA algorithm's performance, 30 independent iterations were conducted, with 110 wolves and 10 internal iterations. The results revealed that the algorithm achieved a maximum objective function value of 0.0025641 in 28 out of 30 runs, indicating strong numerical stability and the ability to reproduce outcomes under identical experimental conditions consistently. The arithmetic mean of the fitness values was 0.00256109, and the median (0.0025641) matched the maximum value itself, reflecting a distribution tightly centered on the optimal value with no significant deviations. A very low standard deviation of 1.128e-05 further supports the observation of minimal dispersion, emphasizing the robustness of the algorithm and its reduced sensitivity to the stochastic nature typical of population-based metaheuristics, as shown in Figure 7. The minimum fitness value of 0.00251889 was observed in only two out of the 30 runs, representing the lowest performance recorded. Although slightly lower than the maximum, this difference is minor and may lead to local optima or reduced population diversity during early iterations, limiting the algorithm's exploratory effectiveness [35], [36]. Nevertheless, the rarity of such deviations reinforces the algorithm's overall consistency and its ability to maintain high performance across multiple runs.

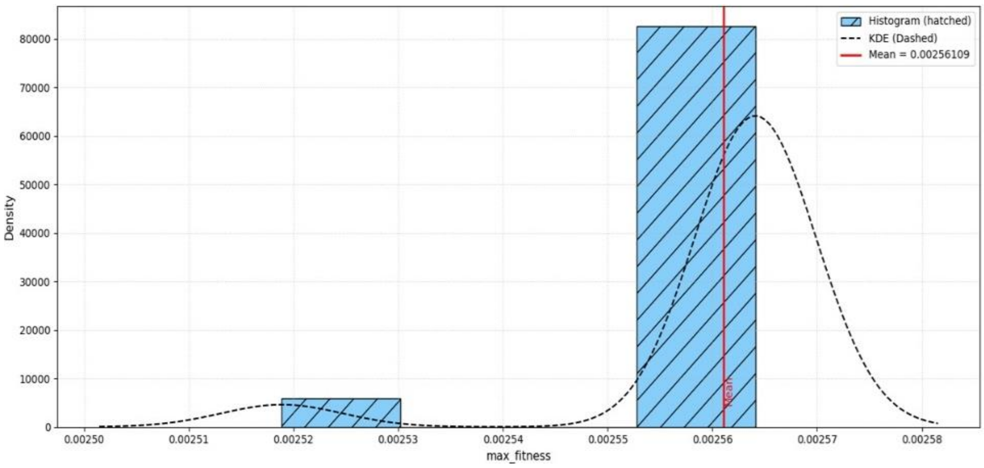

Figure 7. Statistical stability analysis of DGWOA based on max fitness performance

4. CONCLUSON

This research has shown the efficacy of an upgraded DGWOA, augmented with machine learning principles, in addressing fault detection and diagnostic issues in industrial systems. The proposed method was validated using real-world data from a photovoltaic (PV) system, wherein continuous variables were discretized to generate interpretable classification rules. The DGWOA successfully produced four classification rules, one representing normal operating conditions and three corresponding to fault states (F1, F2, and F3), achieving an overall classification accuracy of 99.48% and a precision of 100%. For a comprehensive assessment of the robustness and reliability of the proposed approach, two independent comparative evaluations were conducted. The first involved a set of well-established classification algorithms referenced in prior studies, while the second focused on rule-based classifiers available within the Weka platform. In both cases, the DGWOA demonstrated superior performance, highlighting its capacity to generate accurate and generalizable classification rules in complex diagnostic scenarios. Moreover, a statistical stability analysis based on the maximum fitness values was performed, further confirming the algorithm's numerical consistency and resilience to stochastic variation, which is often inherent in population-based metaheuristics. These findings underscore the effectiveness of DGWOA not only in achieving high classification accuracy but also in maintaining stable behavior across multiple runs. Future work will extend the application of DGWOA to various industrial domains, including wind energy systems and electric motors. Subsequent studies will focus on evaluating its scalability with large-scale datasets and investigating its integration with advanced intelligent optimization and learning techniques to enhance diagnostic performance in complex and dynamic industrial environments.

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AUTHOR CONTRIBUTIONS STATEMENT

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C	:	**C**onceptualization	I	:	**I**nvestigation	Vi	:	**Vi**sualization
M	:	**M**ethodology	R	:	**R**esources	Su	:	**Su**pervision
So	:	**So**ftware	D	:	**D**ata Curation	P	:	**P**roject administration
Va	:	**Va**lidation	O	:	Writing - **O**riginal Draft	Fu	:	**Fu**nding acquisition
Fo	:	**Fo**rmal analysis	E	:	Writing - Review & **E**diting			

CONFLICT OF INTEREST STATEMENT

The authors affirm that they have no conflicts of interest.

DATA AVAILABILITY

The dataset used in this research, entitled "Fault Detection Dataset in Photovoltaic Farms," is freely accessible on Kaggle and can be found at: *https://www.kaggle.com/datasets/amrezzeldinrashed/fault-detection-dataset-in-photovoltaic-farms*.

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