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FEATURE SELECTION USING SPARSITY-AWARE DIFFERENTIAL EVOLUTION FOR ACCURATE DEFECT DETECTION IN PHOTOVOLTAIC MODULES

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Abstract

The efficacy of the photovoltaic (PV) modules is affected by the presence of defects in the modules, therefore monitoring of the PV modules is imperative to ensure reliability and longevity of modules. In this study the features are extracted using histogram of gradients (HOG) and then a novel Sparsity Aware-Differential Evolution algorithm (SA-DE) based feature selection method is introduced for defect classification in electroluminescence (EL) images of PV modules. Several other optimization techniques, such as Genetic Algorithm (GA), Bayesian Optimization (BO), and Ant Colony Optimization (ACO) showed unsatisfactory performance for feature selection. The proposed SA-DE approach exhibits better efficiency in terms of feature selection and defect detection. It is obvious from the results that the method proposed demonstrates superior performance than GA, BO and ACO by achieving an average accuracy of 96 %. A comparative analysis of different optimization methods using Support Vector Machine (SVM) with k-fold cross-validation is also provided to highlight the superiority of the proposed method. Also, the work proposed here is aligned with the United Nations' Sustainable Development Goals (SDGs), particularly SDG-7 by promoting sustainable energy solutions through improved fault detection in solar modules.

Keywords: Defect detection, Electroluminescence images, Feature selection, Differential Evolution, Machine Learning.

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1. Introduction

The increasing dependence on solar energy requires time-to-time monitoring of PV modules to improve the durability and efficiency of the modules. During the manufacturing process or during installation of the modules there are certain types of irregularities that are introduced in the modules that have an adverse impact on the efficiency and overall life of the module[1],[2]. Also, if the modules are not monitored after installation on a regular basis the environmental factors like dust, hailstones etc. can also impact the module efficacy[3]. High resolution electroluminescence images of PV modules are widely used for identifying the defects such as cracks, broken fingers in the PV modules [4],[5]. EL images are captured by applying forward bias to the PV modules and the defect -induced variations are visible in the luminescence of EL image which helps in fault detection and performance assessment of the modules before installation or during maintenance.

The EL images are high-dimensional and some features are redundant and extracting the most relevant features from the EL images is a challenging task. So, an effective feature selection process is required for efficient defect detection and classification in PV modules. The method of choosing the features ensures that only the relevant discriminative features are selected from the available pool of features thereby improving the defect detection process and reducing the computational overhead [6],[7]. Features selection strategies can be categorised as: Filter, Wrapper, Embedded and ensemble methods. Traditional feature selection techniques, such as manual thresholding or statistical methods, may not always lead to the optimal results so it becomes necessary to use the advanced optimization techniques for fine-tuning the selection process and improving defect classification accuracy.

The key contributions of this research work are:

1. A novel Sparsity Aware-Differential Evolution Algorithm (SA-DE)-based feature selection method to enhance the efficiency of PV modules by detecting and classifying defects. The work aligns with the sustainable development goal (SDG-7) by improving PV module quality, ensuring sustainable energy generation, and minimizing economic losses.

2. This study contributes a novel dataset of EL images acquired from PV modules which can be used as a significant resource for developing and evaluating defect detection algorithms.

3. A comparative analysis with the state-of-the-art methods is presented to give an insight into the superiority of the proposed method.

The organisation of the remaining paper is as follows: 'Related Works' section briefly gives the literature review of the existing methods. 'Methodology' section provides an outline of the proposed framework. The experimental results and discussion are followed by the methodology section. Lastly, the conclusion and future scope of the work is discussed in the section 5.[8]

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2. Related Works

Feature selection plays a significant role in optimizing machine learning models as it reduces dimensionality, enhances computational efficiency, and increases classification accuracy. Many researchers explored the optimal feature selection in domains such as facial recognition, software defect prediction, and image-based defect detection. Broadly, the feature selection techniques are categorized into filter, wrapper, and embedded methods [9].

Filter methods, such as Chi-Square, Relief and correlation-based evaluate the relevance of features based on statistical scores without involving any learning algorithm, making them fast and scalable. In [7] the authors discussed the Relief based feature selection methods for different applications and they concluded that the Relief based algorithms constitute a robust category of feature selection methods that effectively balance the ability to identify complex patterns, adaptability to various data types, and computational efficiency. Researchers in [10] used Chi-square and ReliefF methods for recognizing facial expressions and established that KNN yielded the highest classification performance.

Wrapper methods assess subsets of features by actually training a model and selecting features based on performance metrics, which often results in better accuracy but computational cost is increased. The algorithms inspired by the biological systems also called as Swarm Intelligence (SI) algorithms are widely used in applications of social and business domain and there is an increased application of such algorithms in image processing and object detection and classification [11]. SI based algorithms can reach the global optima in an efficient and parallel manner. In [12] the authors discussed the insect-based and bird-based algorithms for optimization.

In embedded methods feature selection is integrated into the model training process itself, for example, the LASSO and decision tree algorithms strike a balance between efficiency and predictive power. In their work in [13] the authors used different feature selection methods including embedded methods for feature selection in the medical domain.

In [14] the authors discussed an embedded feature selection method and proposed a weighted Gini index for handling imbalanced classification problems.

Apart from the individual methods of feature selection, ensemble feature selection techniques have been noted for their capability to combine the benefits of multiple algorithms. These ensemble approaches, whether through parallel or sequential combinations, often lead to improved classification performance and generalization across diverse datasets. The authors in [15] suggested an ensemble feature selection method utilizing sort aggregation and examined the impact of combining features using arithmetic and geometric mean aggregation strategies. The sorting-based ensemble method of feature selection proposed in this study achieved the highest performance across all three datasets (sonar, hcc-survival and musk) and with a value of 0.1 for threshold, AUC scores of 0.873, 0.840, and 0.859 are achieved respectively. They concluded that ensemble feature selection outdoes individual feature selection methods from the perspective of accuracy and robustness.

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In the study, [16] a deep learning-based multi-feature fusion approach was proposed that combines global features (2DPCA) and local texture features (LBP), resulting in significantly improved recognition accuracy. The use of CNN for training on fused features has demonstrated strong potential, achieving over 90% accuracy in large-scale environments.

To enhance performance, authors in [17] also explored ensemble feature selection techniques by combining results from various selection methods either in parallel or sequentially. They highlighted that while ensemble approaches typically yield better classification accuracy than individual methods, the improvement may not always be substantial when compared to the top-performing standalone technique.

In [18] the authors proposed a method in which feature selection is done on the basis of different filters namely, information gain, Chi square, gain ratio, mReliefF and SymmetricUncertainty to get an optimal feature subset and then the feature subset is assessed on three different datasets using , support vector machines, decision trees and random forests. Through these methods the authors were able to overcome the local optima problem for high dimensional data.

The research done in [19] highlights the applicability of hybrid particle swarm optimization (PSO) and genetic algorithm (GA) based approach for optimal selection of features in seven different types of datasets. It is concluded that the hybrid PSO-GA based algorithm shows superior performance to other methods of feature selection used in the work. One of the limitations in using PSO is high dimensionality of the image data which needs to be addressed.

A comparative analysis of five SI based optimization algorithms namely, ant colony optimization, sparrow search optimization, bat algorithm, salp optimization and PSO is done by researchers in [20] for different image processing applications like image segmentation, detection and classification.

A Genetic Algorithm-based feature selection combined with ANN classifier is proposed in [21] for effective and low-computation fault diagnosis in grid-connected PV systems under varied fault conditions.

In the work done in [22] the author used GA for feature selection and PSO for fine tuning the feature selection prior to applying the neural network for prediction of software defects.

In one of the recent studies [23] the authors proposed a comprehensive system for detecting and classifying defects in PV modules EL images. By combining image preprocessing, feature fusion, and a novel feature selection technique (chaotic-based BOA), followed by a hybrid classification model, the system achieved impressive accuracy and significantly outperformed existing methods in multiple performance metrics.

In [24] the authors demonstrated fault detection in solar panel cells by combining deep learning with electroluminescence (EL) imaging. Using a custom dataset of monocrystalline and polycrystalline cells with various defect types, the researchers achieved impressive accuracy—97.82% and 96.29% respectively—using the lightweight SqueezeNet architecture.

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The researchers in [25] fused a global attention module into YOLOv5 for automatic defect detection in PV modules. They also added an adaptive feature space fusion to capture the spatial and semantic features' information and reported a mean average precision of 0.77 in their work.

To handle the data scarcity/imbalance issue in [26] the authors proposed a generative adversarial network for augmentation of data and a CNN for defect detection after augmentation. They substituted the non-maximum suppression (NMS) loss function with Distance Intersection over Union (DIoU). However, such methods require heavy computational resources and are very time consuming.

In [27] the researchers used two deep learning architectures for feature representation- InceptionV3 and ResNet-50 and then another deep network for classifying the EL images into defective and non-defective cells.

2.1 Research Gap and Motivation

After an in-depth review of existing literature, the authors identified key gaps, particularly that significant attention has been given to feature selection in domains such as facial recognition, disease prediction etc., the application of feature selection methods to electroluminescence (EL) images of PV modules remains largely unexplored and presents a promising research opportunity.

Although significant progress has been made in feature selection, existing approaches suffer from computational inefficiency, lack of adaptability to new defect patterns, and over-reliance on handcrafted features. To handle these limitations, this study recommends a novel Sparsity Aware Differential Evolution based (SA-DE) feature selection approach with SVM and 5-fold cross validation to improve defect classification accuracy in EL imaging.

Table 1 provides a summary of existing methods while highlighting the novelty of the proposed approach.

Table 1: Comparison of Feature Selection Methods for Defect Detection

Method	**Description**	**Advantages**	**Limitations**	**References**
Filter Methods	Features selected on the basis of statistical relevance	Fast, scalable, independent of classifiers	Ignores feature dependencies, may select irrelevant features	[6], [7], [10], [28], [29]
Wrapper Methods	Uses a predictive model to evaluate feature subsets	Higher accuracy, considers feature dependencies	Computationally expensive, prone to overfitting	[30], [20], [21] [11], [12], [31]

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Embedded Methods	Feature selection occurs during model training	Efficient balances accuracy and computational cost	Limited flexibility, depends on the model used	[14], [32]
Ensemble approaches	Combines two or more methods to optimize selection	Improves robustness, reduces redundant features	Increased complexity may require fine tuning	[17], [18], [15], [33]
Deep learning-based feature selection	Uses neural networks to learn optimal feature representations	Handles complex patterns, suitable for large datasets	High computational cost, requires large labelled datasets	[22], [34], [35]
Proposed Method- **Sparsity Aware-Differential Evolution algorithm (SA-DE) based feature selection method**	A novel optimization-based method for feature selection. No prior research has explored the integration of Sparsity into DE for PV EL image defect detection.	Enhances accuracy, reduces redundancy, adapts to new defect patterns and suitable for high dimensional data.	Require fine tuning of multiple models	This study

3. Methodology

The main emphasis of this research is to select the optimal features that lead to high performance in detection of PV modules defects with the help of EL images. The proposed framework comprises preprocessing and augmentation, feature extraction using HOG, feature selection using different methods and defect detection using SVM with 5-fold cross-validation. Figure 1 depicts the visual outline of the proposed methodology.

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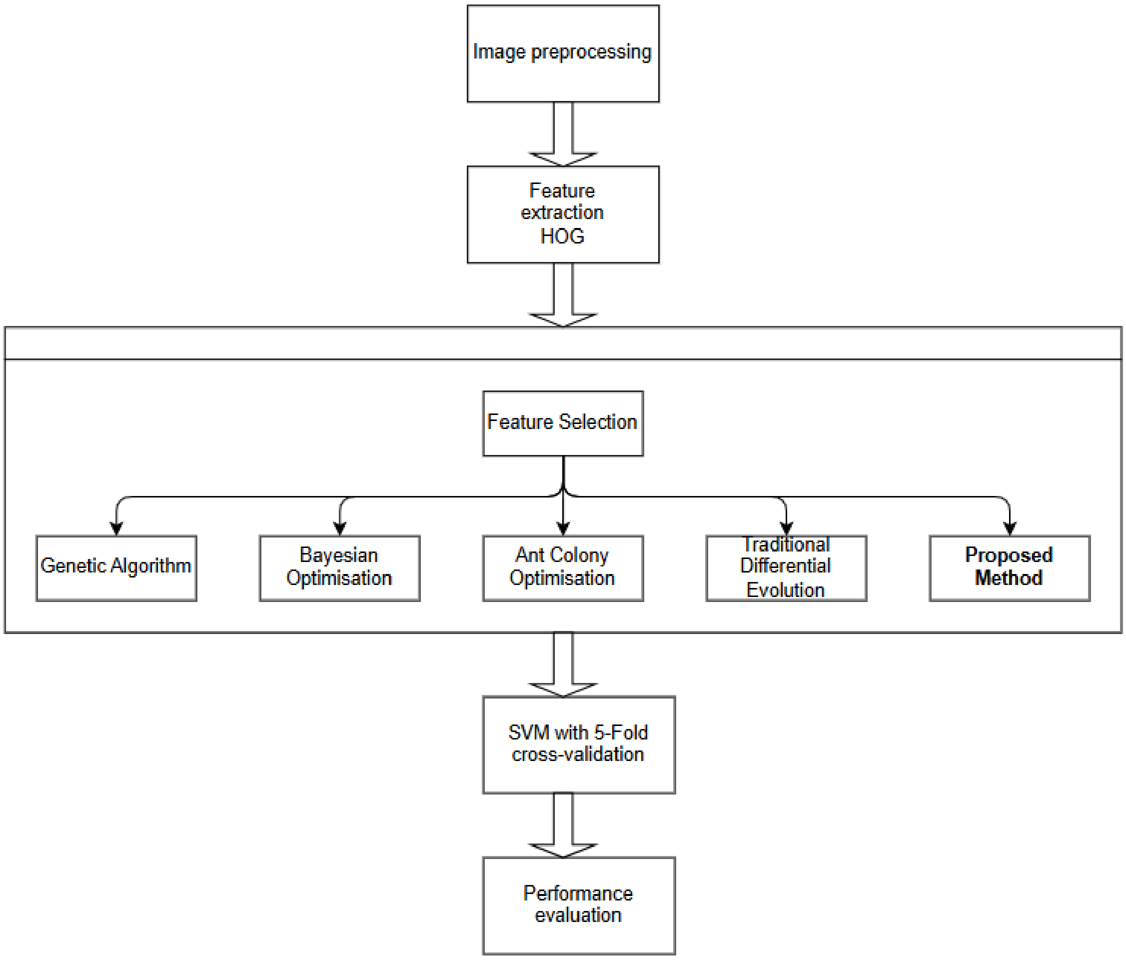

Figure 1. Visual outline of the proposed methodology

3.1 Dataset Description

The study utilizes an EL image dataset provided by the National Institute of Solar Energy (NISE), India. 100 images are extracted from three modules and resized to 300x300 pixels with a bit depth of 32. The dataset comprises 66 defective and 54 non-defective cell images and organized into two folders: **Defective** and **Non-Defective**. Sample images are shown in figure 2 below. The images are resized to 128x128 so that the computational complexity is reduced. To take care of the small dataset size offline data augmentation is done.

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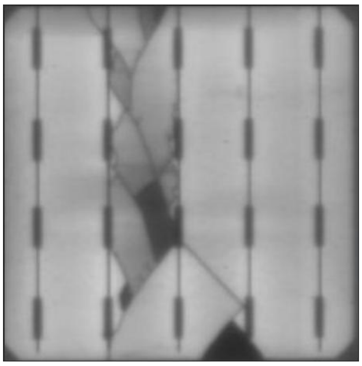
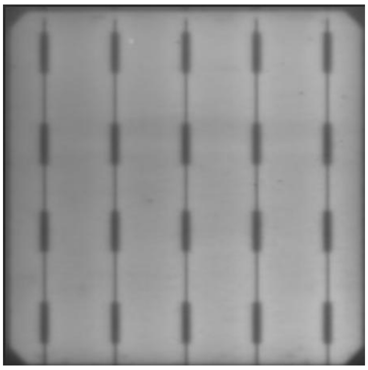


(a)



(b)

Figure 2. (a) Defective and (b) Non-defective EL image

3.2 Feature Extraction

The information relevant to defect detection is captured using the Histogram of Oriented Gradients (HOG) features [36]. HOG descriptors are extensively used in image classification tasks due to their capability to represent structural variations effectively [37]. The reason for selecting HOG for feature extraction in our work is that there are texture variations and discontinuities in the EL images and HOG descriptors capture this information by analysing the gradient orientations.

The HOG descriptor is used to characterize the shape and structure in images based on the distribution of edge orientations. To identify the edge directions the horizontal and vertical gradients are computed as:

$$G_x = I(x+1, y) - I(x-1, y) \tag{1}$$

$$G_y = I(x, y+1) - I(x, y-1) \tag{2}$$

where I (x, y) is the pixel intensity at position (x, y).

For each pixel the magnitude and orientation of gradient are computed as:

$$M(x, y) = \sqrt{{G_x}^2 + {G_y}^2} \tag{3}$$

$$\Theta(x, y) = \arctan\left(\frac{G_y}{G_x}\right) \tag{4}$$

The image is partitioned into small non-overlapping cells of 8x8 pixels and in each cell a histogram of gradient orientations is created. To handle variations in lighting and contrast, the neighbouring cells are grouped into blocks of 2×2 cells i.e. 16×16 pixels. Then the histogram vector of each block is normalized using L2 norm. The normalized histograms from each block are then combined to form the final HOG feature.

3.3 Optimization-Based Feature Selection

To improve classification accuracy, different feature selection methods were employed:

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A. Genetic Algorithm (GA)

Genetic Algorithm (GA) is an optimization approach using evolutionary search which is inspired by the process of natural selection [38]. It is suitable for feature selection tasks in high-dimensional datasets where an exhaustive search is computationally infeasible. GA begins with a population of candidate solutions (chromosomes), each represented as a binary string where a selected feature is indicated by 1 and an unselected feature by 0. A performance metric is used to evaluate the fitness of each chromosome and often classification accuracy is used as the metric. The genetic operators: selection, crossover, and mutation are applied and the population evolves over generations and the best feature subset is selected as shown in the flowchart in figure 3. The fitness function $f(x)$ is defined as:

$$f(x) = \alpha \,.\, Accuracy - \beta \,.\, \frac{|x|}{n} \tag{5}$$

where $|x|$ is the number of features selected, n is the total number of features, and α , β are weight factors balancing accuracy and subset size. Over successive generations, GA promotes the survival of feature subsets that lead to better classification performance and reduced dimensionality, helping to avoid overfitting and improve model generalization.

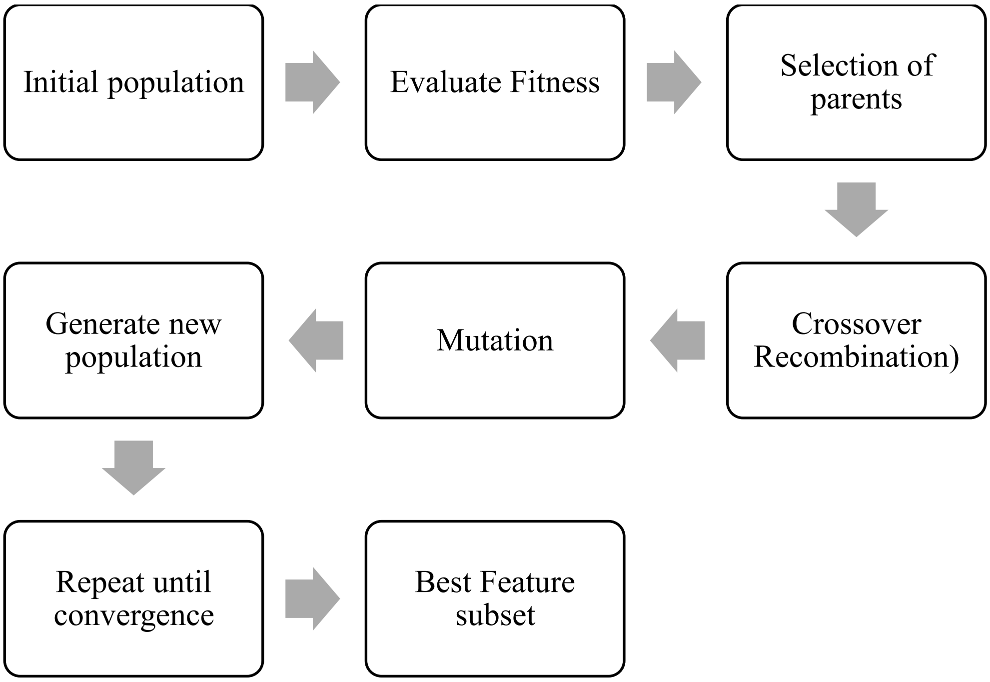

Figure 3. Feature selection using GA

B. Bayesian Optimization

When hyperparameter tuning is required, Bayesian optimization (BO) can be an effective method for feature selection and it can also benefit downstream tasks [39]. BO is a model-based optimization technique that proficiently guides the search for optimal feature subsets in

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computationally expensive tasks such as in PV module defect detection using EL images. BO builds a probabilistic model which is typically a Gaussian Process (GP) to estimate the objective function and uses an acquisition function to decide where to sample next. The goal is to balance exploration (trying unknown areas) and exploitation (focusing on areas with known good results). Mathematically, given an objective function $f(x)$ that is expensive to evaluate, BO maintains a posterior distribution $P(f|D)$ over functions based on data D, and selects the next input x_{next} by optimizing the acquisition function $a(x)$, such that:

$$x_{next} = \arg\max_{x} a(x|P(f|D)) \tag{6}$$

This approach iteratively refines the model, ensuring that optimal parameters or feature combinations are found with minimal evaluations. In fault classification or defect detection tasks, Bayesian Optimization significantly enhances classifier performance by choosing the relevant features and hyperparameters. Its adaptability and efficiency make it a powerful tool in automated machine learning pipelines.

C. **Ant Colony Optimization (ACO)**

Ant Colony Optimization (ACO) is a population-based metaheuristic inspired by the searching behaviour of real ants, where artificial agents (ants) construct solutions by exploring paths in a feature space [40]. In the context of feature selection, each ant builds a candidate feature subset by probabilistically choosing features based on pheromone trails and heuristic desirability. The **objective function** to assess the quality of a particular feature subset is $f(x)$.

The probability P_i^k that ant k selects feature i is calculated using both the pheromone τ_i and a heuristic value η_i (e.g., correlation or relevance):

$$P_i^k = \frac{[\tau_i]^{\alpha}.[\eta_i]^{\beta}}{\sum_{j \epsilon F}[\tau_i]^{\alpha}.[\eta_i]^{\beta}} \tag{7}$$

where:

- τ_i is the pheromone level for feature i,
- η_i is the heuristic information (e.g., mutual information score),
- α, β control the impact of pheromone and heuristic information,
- F is the set of all available features.

As ants construct and evaluate feature subsets, the pheromone trails are updated to reinforce better-performing subsets, leading to convergence toward optimal or near-optimal solutions over iterations. ACO offers robust search capabilities and is particularly effective in complex, high-dimensional feature spaces such as in PV module defect classification tasks.

D. Proposed Sparsity Aware-Differential Evolution Algorithm (SA-DE)

The EL images used for defect detection in photovoltaic (PV) modules has a high-dimensional feature space. Selecting the most relevant subset of these features is crucial to confirm robust classification performance, computational efficiency, and model interpretability. This work proposes a novel feature selection methodology based on Differential Evolution (DE) with an

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embedded sparsity constraint, specifically designed to address the shortcomings of traditional DE approaches in this domain.

Traditional Differential Evolution is a very common and widely-used population-based evolutionary algorithm, known for its simplicity, global optimization capabilities, and strong performance across a range of continuous optimization problems. In feature selection tasks, each individual in the DE population typically represents a candidate feature subset encoded as a binary vector. The objective is to evolve this population to maximize a fitness function, defined here in terms of classification accuracy with the selected features.

However, traditional DE methods suffer from the following drawbacks when applied to high-dimensional image-based feature spaces such as those derived from EL images:

1. **No Control Over Feature Sparsity**: Standard DE optimizes for accuracy alone. In the absence of regularization, the algorithm tends to select a large number of features, including redundant or noisy ones, which leads to overfitting and bloated models.

2. **High Computational Burden**: Conventional DE implementations often use large population sizes and high iteration counts to explore the search space thoroughly. This leads to increased computation time and memory usage, making them impractical for real-time or resource-constrained environments like Google Colab.

3. **Low Interpretability and Poor Generalization**: Feature subsets selected without sparsity constraints are harder to interpret and may fail to generalize across datasets, especially when irrelevant or weakly correlated features are included.

Proposed DE with Sparsity Penalty

To address these limitations, we propose a **lightweight and sparsity-aware variant of the Differential Evolution algorithm**. The novelty of our approach lies in two major improvements:

- **Sparsity-penalized Fitness Function**: A sparsity term is incorporated into the fitness function to discourage the selection of excessive features.

- **Lightweight Execution Strategy**: The algorithm is designed to operate efficiently with smaller population sizes and fewer generations, making it computationally feasible for environments with limited resources.

The modified sparsity-aware fitness function is defined as:

$$f(x) = Accuracy(x) - \lambda . \frac{\|x\|_0}{D} \quad (8)$$

Where: $x \in \{0,1\}^D$ is the binary feature mask,

$\|x\|_0$ denotes the number of selected features(L0-norm),

D is the total number of features,

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λ is the sparsity penalty coefficient that governs the trade-off between performance and model simplicity.

This formulation enables the algorithm to favour solutions that balance high classification accuracy with compact, interpretable feature subsets. The value of λ can be tuned based on the problem setting to enforce stronger or weaker sparsity.

Algorithm: Differential Evolution with Sparsity for Feature Selection

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Input:

- *Population size: NP*
- *Number of generations G*
- *Crossover rate CR*
- *Scaling factor F*
- *Number of features D*
- *Sparsity penalty coefficient λ*

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1. Initialization:

Population is initialized randomly: $P = \{x_1, x_2, \ldots\ldots, x_{NP}\}$, *where each individual* $x_i \in \{0,1\}^D$ *represents a binary vector representing selected features.*

For each x_i, *evaluate the sparsity-aware fitness function:*

$$f(x) = Accuracy(x) - \lambda \,. \frac{\|x\|_0}{D}$$

2. Evolution Loop (Repeat for g=1 to G):

For each individual $x_i \in P$:

Mutation:

Randomly select three distinct indices $r1, r2, r3 \neq i$

Generate mutant vector:

$$v_i = x_{r1} + F.(x_{r2} - x_{r3})$$

Apply a sigmoid transformation and binarization:

$$v_i[j] = \begin{cases} 1 & if\ \sigma(v_i[j]) > rand() \\ 0 & otherwise \end{cases} \qquad where\ \sigma(z) = \frac{1}{1+e^{-z}}$$

Crossover:

Create trial vector u_i *as:*

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$$u_i[j] = \begin{cases} v_i[j] & if\ rand() < CR \\ x_i[j] & otherwise \end{cases}$$

Fitness Evaluation:

$$f(u_i) = Accuracy(u_i) - \lambda . \frac{\|x\|_0}{D}$$

Selection:

$$x_i = \begin{cases} u_i & if\ f(u_i) > f(x_i) \\ x_i & otherwise \end{cases}$$

3. Output

Return the best individual $x_{best} \in P$ with the highest fitness value.

In EL-based defect detection, the subtle differences between defective and non-defective cells often lie in high-frequency, low-contrast regions. This method's ability to automatically isolate discriminative features—while suppressing irrelevant ones—directly contributes to better classification accuracy and faster inference time. It enables not just detection, but interpretability, which is important for practical applications such as maintenance planning or module rejection in manufacturing.

3.4 Classification using SVM

After different feature selection methods including the proposed sparsity-aware Differential Evolution (SA-DE) approach, the next stage in the defect detection pipeline involves classification.

The reduced feature subset is employed to train the SVM. Defective and non-defective PV module images are labelled accordingly, and the model is trained to distinguish between them based on the selected features. The high-dimensional feature vectors obtained from texture or frequency domain transformations of EL images are ideal candidates for SVM due to its margin-maximizing and regularization capabilities[41],[42].

For this purpose, we used the Support Vector Machine (SVM) which is a widely accepted and strong supervised learning algorithm, particularly effective in high-dimensional spaces such as those derived from EL image features. SVM is a discriminative classifier that constructs an optimal hyperplane that separates the data points of diverse classes with the maximum margin[43]. Given a set of training data:

$$\{(x_i, y_i)\}_{i=1}^{n}, \ \ x_i \in R^d, y_i \in \{-1, +1\} \tag{9}$$

SVM tries to find a hyperplane characterized by weight vector w and bias b, such that:

$$w^T x + b = 0 \tag{10}$$

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This hyperplane should satisfy the following condition for linearly separable data

$$y_i(w^T x + b) \geq 1 \quad \forall_i \tag{11}$$

To find this hyperplane, SVM solves the following convex optimization problem:

$$\min_{w,b} \frac{1}{2}||w||^2 \ subject\ to\ y_i(w^T x + b) \geq 1 \tag{12}$$

In many real-world problems, including EL image-based PV defect detection, data may not be linearly separable. To handle this SVM uses the kernel trick, maps the data into a higher-dimensional space so that a clear boundary can be found that separates different groups.. Common kernel functions include: linear kernel, polynomial kernel and RBF kernel. In our implementation, we used the RBF kernel due to its ability to handle non-linearly separable patterns in EL image features and its effectiveness in binary classification tasks.

Cross-validation is an evaluation technique that is used to measure generalizing capability of a model to an independent dataset by partitioning the data into training and validation subsets [44]. In this work five-fold cross-validation is used for robust and unbiased evaluation of the model. The dataset comprising EL images was split into five equal parts or folds. In each fold, the model was trained on four subsets and the last one was used for validation. The process is iterated five times, with each subset acting as the validation set in one of the iterations. Finally, the average of the performance metrics across all five folds is reported which demonstrates a reliable assessment of the model's capability to generalize across unnoticed PV module defect patterns.

4. Results and Discussion

The comparative performance of various feature selection techniques applied to the classification task is summarized in Table 2. The evaluation was conducted using the performance metrics, namely accuracy, precision, recall, and F1-score [45]. Evidently, the proposed Sparsity-aware Differential Evolution (SA-DE) method consistently outperformed all other approaches across these metrics.

Traditional evolutionary algorithms like Genetic Algorithm (GA) and Ant Colony Optimization (ACO) demonstrated reasonable performance, achieving accuracies of 0.86 and 0.83, respectively. While these methods captured important features, they exhibited limitations in either precision or recall, reflecting trade-offs in their selection strategies. For instance, GA achieved a recall of 0.92 but a slightly lower precision of 0.80, indicating potential over-selection of features or redundancy in the selected subset.

Bayesian Optimization, a probabilistic model-based method, showed strong recall (0.93) similar to GA but maintained a modest precision of 0.80 and overall accuracy of 0.83. Although it effectively identified informative features, its performance was not optimal in balancing false positives and false negatives.

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In contrast, Traditional Differential Evolution (DE) demonstrated a significant leap in performance, reaching an accuracy of 0.92 and an F1-score of 0.89. This suggests that DE's exploratory power is well-suited for navigating high-dimensional feature spaces like that of EL images of PBV modules. However, traditional DE does not explicitly consider sparsity, which is a key requirement in real-world scenarios where interpretability and computational efficiency are significant.

The proposed Sparsity-aware DE builds upon this strength by introducing a sparsity-driven mechanism that promotes the selection of compact, non-redundant feature subsets without compromising classification performance. This innovation led to the maximum accuracy of 0.96, with precision, recall, and F1-score reaching 0.91, 0.98, and 0.95, respectively. The elevated recall indicates that the method is particularly effective in identifying true positives, a crucial factor in defect detection and similar applications.

Table 2: Comparison of different Feature Selection Methods with the proposed method

Feature selection method	**Accuracy**	**Precision**	**Recall**	**F1-score**
Genetic Algorithm	0.86	0.80	0.92	0.86
Bayesian Optimization	0.83	0.80	0.93	0.86
Ant Colony Optimization	0.83	0.79	0.88	0.83
Traditional DE	0.92	0.85	0.86	0.89
Sparsity aware-Differential Evolution (SA-DE) (Proposed Method)	**0.96**	**0.91**	**0.98**	**0.95**

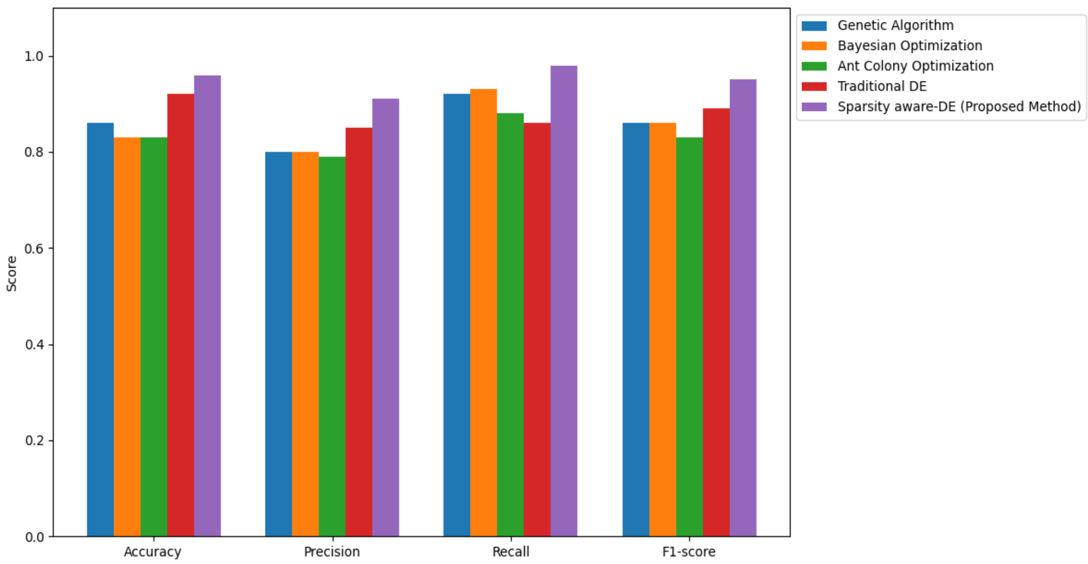

Figure 4. Performance comparison of different feature selection methods with the proposed method

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These results clearly demonstrate the novelty and efficacy of integrating sparsity-awareness into the DE framework as depicted in Figure 4 also, which not only enhances predictive performance but also supports model simplicity and interpretability. The proposed approach thus holds significant importance in domains where both performance and transparency are essential.

Table 3. Comparison of the proposed work with the existing works:

Method	Accuracy
Light Convolutional Neural Network [46]	93.02 %
SVM classifier [47]	82.44 %
Convolutional Neural Network [47]	88.42 %
Hybrid Fuzzy Convolutional Neural Network [48]	88.38 %
Sparsity aware-DE (Proposed Method) based feature selection with SVM classifier	**96 %**

The work introduces novelty by the integration of a sparsity-penalization in Differential Evolution (DE) framework to optimize classification accuracy and feature subset compactness. Unlike conventional DE-based feature selection methods where accuracy is the only parameter which is significant, the proposed approach maintains a dynamic record of non-dominated solutions thereby creating a balance between performance and model simplicity. This dual-objective strategy, applied to electroluminescence (EL) images of photovoltaic modules, enhances defect classification while reducing computational overhead, making the method both effective and resource-efficient for real-world deployment.

5. Conclusion

This paper presents a novel framework for defect detection of PV modules by using EL images. The EL images from dataset taken form NISE are resized and the dataset is augmented to increase the size of the dataset for feature extraction. HOG is used for feature extraction that enhances the model's capability to capture defect-relevant patterns in EL images. After feature extraction different feature selection methods are applied for feature selection namely, Genetic Algorithm, Bayesian Optimization, Ant Colony Optimisation and the traditional differential evolution. Then the Sparsity Aware Differential Evolution Algorithm (SA-DE) is proposed for optimal feature selection in EL image-based PV module defect detection. By incorporating the sparsity penalty in fitness function, the proposed framework balances the classification accuracy with feature reduction leading to an efficient and computationally efficient method. The 5-fold cross validation along with SVM classifier is used validate the efficacy of the proposed framework. The results are clearly indicating that the proposed method surpasses all

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other methods as well as the existing works as given in Tables 2 and 3 in different performance metrics. The proposed method achieves an accuracy of 96%.

Future research will emphasize on the advanced data augmentation methods like generative adversarial networks and contrastive learning to synthetically increase the size of dataset. Deep learning-based ensemble models can be explored for further improving the defect classification. Real-time deployment is achievable through the lightweight models as proposed in this study also, which are well-suited for on-device processing and enable efficient PV module inspection in field environments. This directly supports UN SDG 7 (Affordable and Clean Energy) by improving PV module reliability, advancing sustainable energy practices, and fostering wider adoption of solar technologies.

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