Multi-Objective Optimization for a Robust Deep Learning Model in Plant Image Classification: A Review with Trends, Challenges, and Future Directions

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ABSTRACT

This paper presents a comprehensive review of Multi-Objective Optimization (MOO) techniques for the enhancement of Deep Learning (DL)-based plant image classification by jointly addressing competing objectives such as classification accuracy, inference speed, generalization capability, and computational efficiency. Unlike existing research that treats DL architectures or optimization strategies in isolation, this work systematically integrates MOO principles with state-of-the-art DL models across the entire learning pipeline, including feature selection, hyperparameter tuning, and neural architecture search. Key evolutionary and hybrid MOO algorithms - such as NSGA-II, MOEA/D, MOPSO, and SPEA2 – were critically analyzed with respect to their applicability in agricultural imaging tasks. Practical challenges were further highlighted, arising from environmental variability, dataset imbalance, and field deployment constraints. By synthesizing current trends, identifying research gaps, and outlining future directions, this study positions MOO as a promising paradigm for developing robust, resource-aware, and field-deployable AI systems for precision agriculture.

Keywords-detection; classification; Deep Learning (DL) model; hybrid approaches; plant disease

I. INTRODUCTION

Global food security is under increasing pressure due to the rapid population growth and agricultural instability. Plant diseases, stemming from biological pathogens and environmental stressors, pose a significant threat to sustainable agriculture, reducing both crop yield and quality across diverse species [1]. Although early and accurate detection of these diseases is appropriate for effective intervention, traditional diagnostic methods have been proven to be labor-intensive, error-prone, and often delayed. Advances in Deep Learning (DL) [2], particularly Convolutional Neural Networks (CNNs), have enabled the automated plant disease detection through high-accuracy image classification based on visual features such as color, texture, and shape. Despite their promise, real-world deployment of these models remains challenging due to environmental variability, data imbalance, and scalability constraints [3]. This review is motivated by the need for intelligent agricultural systems that integrate DL with robust optimization strategies to enable reliable and early disease diagnosis, thereby supporting informed decision-making in precision agriculture.

Image-based diagnosis using Artificial Intelligence (AI) and DL has emerged as a powerful alternative, enabling early detection, large-scale monitoring, and timely intervention. Figure 1 illustrates a process flow diagram of DL in plant disease analysis using publicly available benchmark datasets [4, 5].

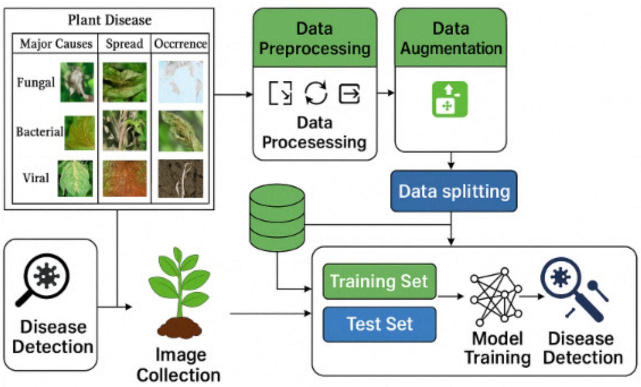

Fig. 1. Process flow diagram of DL in plant disease analysis.

The plant disease images used in these studies were obtained from the publicly available PlantVillage dataset, a widely adopted benchmark dataset in agricultural image analysis [6]. This dataset contains high-resolution RGB images of healthy and diseased plant leaves collected under controlled conditions, covering multiple crop species and disease categories. PlantVillage is publicly accessible and has been extensively used for training and evaluating DL models in plant disease classification due to its standardized annotations and class diversity. Using this dataset ensures reproducibility and facilitates fair comparison with existing state-of-the-art methods.

Research has demonstrated that learning high-frequency information significantly improves hyperspectral pan-sharpening and classification by enhancing edge preservation and sample discrimination [7]. DL models, including CNNs, Deep Belief Networks (DBNs), Recurrent Neural Networks (RNNs), and Sparse Autoencoders (SAEs), have been widely applied for plant species recognition and disease detection [8]. High-accuracy crop disease diagnosis has been achieved using deep CNNs trained on large datasets, enabling smartphone-based global deployment with a reported accuracy of 99.35% [9]. Visualization-driven DL approaches further improve early disease detection, even before visible symptoms appear. Additionally, combining deep features (e.g., VGG19) with handcrafted features has shown performance gains, with Random Forest (RF) classifiers achieving an accuracy of up to 93.73% [10].

II. MULTI-OBJECTIVE OPTIMIZATION IN PLANT IMAGE CLASSIFICATION

Multi-Objective Optimization (MOO) offers an effective framework for addressing the inherently conflicting goals involved in DL-based plant disease detection. Unlike single-objective optimization, which focuses on one criterion, MOO simultaneously balances multiple objectives such as classification accuracy, inference speed, and generalization ability [11]. This approach is particularly relevant for plant image classification, where improving one performance metric often degrades another.

Formally, MOO seeks to optimize multiple objective functions ($f_1(x), f_2(x), \ldots f_k(x)$) under given constraints, yielding a set of Pareto-optimal solutions rather than a single optimum one [12]. A solution is Pareto optimal if no objective can be improved without worsening at least one other objective. The collection of such trade-off solutions forms the Pareto front, which visually represents the balance between competing metrics. For instance, in plant disease classification, highly accurate models often incur higher inference latency, whereas faster models may sacrifice some accuracy. Models lying on the Pareto front represent efficient trade-offs between these objectives.

Pareto optimality plays a crucial role in practical model selection, especially in agriculture, where deployment conditions vary widely. High-capacity models may be suitable for laboratory environments, while lightweight models are preferred for real-time field applications on mobile or embedded devices. By analyzing the Pareto front, researchers can select models that best meet specific operational constraints, such as achieving maximum accuracy within strict latency or hardware limits. Studies have demonstrated the effectiveness of Pareto-based evaluations in agricultural AI, including balancing diagnostic accuracy with mobile hardware constraints and analyzing trade-offs between precision and model complexity using feature reduction techniques such as Whale Optimization [13].

Designing the CNN or transformer architecture itself can be posed as a multi-objective problem. Neural Architecture Search (NAS) algorithms aim to find the optimum network structure (number of layers, filter sizes, skip connections, etc.) for a given task. The incorporation of MOO in NAS means that the search evaluates architectures on multiple criteria. For plant image analysis, one might seek an architecture that maximizes accuracy on disease classification while minimizing computational complexity (FLOPs or parameters) and perhaps maximizing robustness to image noise [14]. MOO-based NAS has been reported in recent studies. For example, one approach used an evolutionary MOO algorithm to evolve CNN architectures, yielding a set of networks where some were very light-weight (suitable for edge devices), and others were larger but more accurate – all lying on a Pareto front of accuracy versus inference speed [15]. Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) is particularly well-suited, as it can decompose the architecture search problem into many scalar sub-problems (each emphasizing a different weighted combination of objectives) and solve them in parallel [16]. This has shown success in high-dimensional architecture searches, where MOEA/D produced more diverse architectures with better trade-offs compared to single-objective or simpler multi-objective methods. Another trend is combining reinforcement learning or gradient-based NAS with MOO [17], allowing faster search of the architecture space while still considering multiple objectives. In total, by applying MOO to NAS, researchers can automatically discover model architectures that are Pareto-optimal; for instance, finding a network that is as compact as possible without dropping below a desired accuracy, which is incredibly valuable for deploying disease detection models on resource-constrained devices.

To summarize these applications, Table I links popular MOO algorithms to their typical uses in DL for plant image tasks.

TABLE I. MOO ALGORITHMS AND TYPICAL APPLICATIONS IN PLANT IMAGE CLASSIFICATION

MOO algorithm	Typical application in DL	Example of use in plant disease tasks
NSGA-II	Hyperparameter tuning; architecture search	Optimizing CNN hyperparameters for accuracy versus size. Selecting network depth vs. accuracy trade-offs.
MOEA/D	Architecture search (high-dimensional objectives)	Evolving CNN structures with many objectives (accuracy, latency, memory). Achieving superior diversity in CNN models for various crops.
MOPSO	Model parameter optimization (multi-criteria PSO)	Tuning training parameters (e.g., learning rate schedules) for accuracy and stability. Requires diversity control to avoid early convergence.
SPEA2	Feature selection; multi-criteria model selection	Selecting optimal feature subsets (maximize accuracy, minimize features). Identifying a portfolio of models balancing precision and recall.

The effectiveness of algorithms, such as NSGA-II and MOEA/D, is highlighted in Table I in terms of managing complex search spaces, involving network architectures and hyperparameters, where balancing performance and computational efficiency is critical. Additionally, MOPSO introduces swarm-based simplicity to multi-objective optimization, although mechanisms are required to preserve solution diversity and prevent premature convergence [18]. SPEA2, which maintains an external archive of non-dominated solutions, is particularly effective for exhaustive tasks such as feature selection and to produce a well-distributed Pareto front [19]. Overall, the application of these MOO algorithms to plant disease classification has yielded more balanced and deployment-ready models by explicitly incorporating real-world constraints during the design stage rather than addressing them post hoc.

However, MOO in agricultural DL presents several challenges, particularly in achieving robustness, real-time performance, and generalization across diverse crops and environmental conditions. Plant image classification is a key application in precision agriculture, supporting early disease detection and informed decision-making. Figure 2 illustrates the pipeline of leaf disease detection, which includes image acquisition, preprocessing, segmentation, feature extraction, and classification, with each stage contributing to the overall performance while introducing competing optimization objectives [20].

This study does not implement a specific leaf segmentation algorithm. The segmentation stage, displayed in Figure 2, represents commonly adopted preprocessing approaches reported in the literature. Authors in [21] provided a comparative analysis of multiple image segmentation techniques, including threshold-based, edge-detection, region-based, clustering, and DL-based approaches. In practice, existing studies typically employ one or a subset of classical image processing techniques, including color thresholding, Otsu's thresholding, edge detection, or K-means clustering, whereas more recent works have adopted DL-based segmentation models, including U-Net and Mask R-CNN, to isolate leaf regions from complex backgrounds [22].

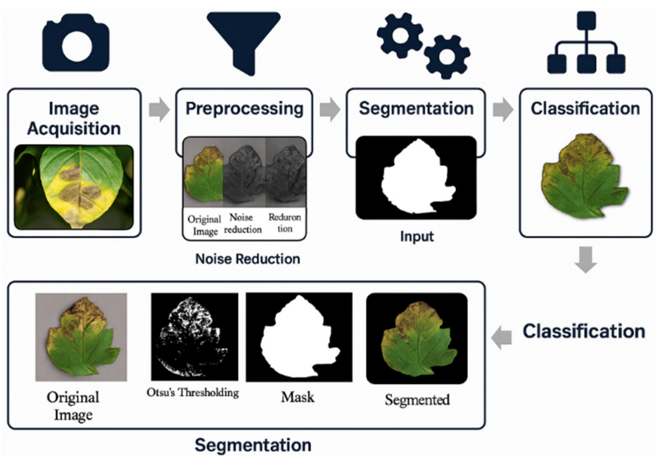

Fig. 2. Leaf disease detection pipeline.

Model generalization across a range of settings is hampered by environmental unpredictability and a lack of datasets [23]. Resource requirements are significantly increased by complex DL architectures [24]. Nevertheless, focusing on accuracy ignores other important variables, such as latency and precision. Furthermore, there are multi-objective trade-offs among performance, efficiency, and overfitting control when adjusting model hyperparameters [25]. These challenges emphasize the necessity of MOO strategies to develop robust, efficient, and scalable models for practical agricultural applications.

III. REAL-TIME PERFORMANCE CONSTRAINTS

A significant challenge for deploying plant disease detectors in the field is meeting real-time requirements. “Real-time” in this context means a model can process images and output a diagnosis instantly or within a few seconds, enabling on-the-spot decision-making (a drone scanning a field or a farmer using a smartphone camera) [26]. Many current models, however, are too slow or resource-intensive for such use. Some high-accuracy models were demonstrated only on desktop GPUs and lack any deployment strategy for real-time operation [27]. Others were trained and tested on single crops (like only apple leaves or only tomato plants), meaning that multiple specialized models would be needed to cover a variety of crops - impractical in real-world farming. Moreover, architectures tested only in controlled settings (greenhouses or labs) often failed to account for the complexities of field deployment, such as the need to process dozens of images per second from a moving drone or to run on a mobile device continuously. From an optimization perspective, achieving real-time performance is inherently a multi-objective problem: one must minimize inference time and model size while maintaining high accuracy [28].

MOO techniques are significant in these cases as researchers can evolve or train models that specifically target efficient operation by including inference speed or model memory footprint as objectives alongside accuracy. For instance, multi-objective NAS has discovered CNN architectures that are lightweight yet reasonably accurate, explicitly trading a few percentage points of accuracy for a 10× faster inference time - a worthwhile trade-off for many applications [17]. Likewise, hyperparameter tuning using MOO can yield configurations that favor faster predictions (by using smaller input image sizes or lower network depth) if required by the deployment scenario. A concrete example is the optimization of YOLOv5 models for speed versus accuracy. Authors in [29] balanced these objectives to create a compact model that still achieved around 90% of the original accuracy but could run on mobile devices in real time.

Figure 3 depicts a typical plant disease detection pipeline, highlighting the stages involved in image preprocessing, feature extraction, and classification. Many existing models are not yet practical for real-time or large-scale deployment despite significant progress in plant disease detection [30-34]. Research has narrowly focused on individual crops, such as tomato [35], which limits their generalizability across different plant species. Others, like the models developed in [34, 35], were tested only in controlled environments without validating performance under real-world field conditions. Some systems, including those in [14, 36], did not scale well and lacked integration with IoT or mobile platforms. Moreover, authors in [5, 11] focused primarily on technical performance while neglecting usability factors such as accessibility, user interaction, and practical deployment in field settings.

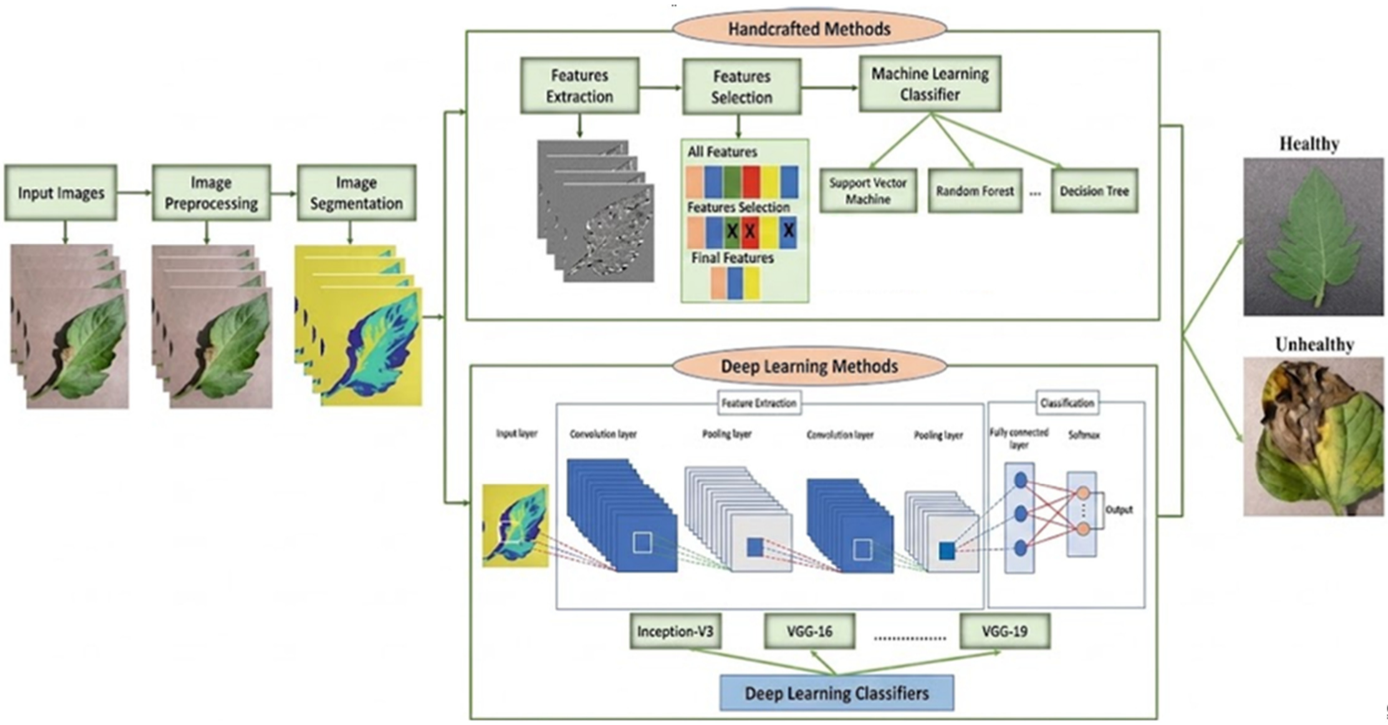

Fig. 3. Plant disease detection pipeline.

A MOO-hybrid algorithm can address these gaps by enabling generalization across crops by optimizing conflicting objectives like accuracy and robustness under diverse field conditions. MOO also balances accuracy and computational efficiency, making models efficient for mobile and edge deployment [37, 38]. It also supports scalable, low-latency architectures and optimizes model selection and hyperparameters based on accuracy, memory, and training time, which is essential for real-time, user-facing plant health systems.

IV. GENERALIZABILITY AND ADAPTABILITY

Plant disease detection models must generalize across different crops, regions, and even evolving pathogen strains. A model trained on one dataset (e.g., images of a given crop in one region) often performs poorly when applied to another crop or location due to differences in appearance, climate, or farming practices.

MOO can contribute to improving the issue of generalization in a couple of ways. First, it can incorporate objectives related to generalization performance, including the enhancement of accuracy on a source or a target dataset, or maximizing a metric that measures robustness to changes (such as variance in performance across different data subsets) [39]. By optimizing these concurrently, the resulting models are more likely to maintain strong performance on unseen conditions. In practice, researchers have started using multi-domain or multi-task training as an implicit multi-objective approach: a model might be trained on multiple datasets (different crops) at once, effectively balancing performance across them. This idea connects with MOO when formalized: each domain's accuracy can be an objective [40]. Advanced MOO applications include domain adaptation using generative methods (like training with both real and synthetic images as separate objectives to ensure that the model learns from both). There is also the concept of few-shot learning objectives - optimizing not just for overall accuracy, but specifically for performance on rare classes or diseases with few examples.

Another aspect of generalizability is transfer learning. Many plant AI models start from ImageNet-pretrained networks, which are then fine-tuned on plant data. However, these pre-trained models may not adapt perfectly because ImageNet images are very different from leaf ones [41]. Multi-objective methods can potentially adjust fine-tuning to maximize plant-specific performance while minimizing forgetting of general features, thus improving transfer across domains. Despite these approaches, achieving broad generalization remains challenging. It often requires larger, more diverse datasets (which are not always available) and clever strategies like data augmentation (e.g., using GANs to generate diverse training images) [42]. MOO can optimize the use of such strategies by balancing data diversity versus training stability. For instance, adding many augmented images can help generalization but might increase training time or noise, so an optimal point must be found. A persistent gap is dynamic objective weighting. As conditions change or new data arrive, how should a model adjust its priorities? Designing MOO frameworks that can adapt weights or objectives over time (e.g., give more weight to generalization if a model starts overfitting) is an open research question. Addressing it will be key to developing models that maintain performance year after year, across different fields and even as new diseases emerge. In conclusion, while MOO provides powerful tools to balance objectives, applying these techniques to plant image classification faces practical challenges in ensuring robustness, speed, and adaptability. A part of ongoing research is to tackle these issues using MOO.

V. MULTI-OBJECTIVE OPTIMIZATION ALGORITHM APPLICATION

Several MOO algorithms have been successfully applied to DL-based plant image classification, NSGA-II, MOEA/D, MOPSO, and SPEA2, each offering different trade-offs between convergence, diversity, scalability, and computational cost.

NSGA-II is the most widely utilized MOO due to its robust non-dominated sorting and crowding-distance mechanisms, providing well-distributed Pareto fronts for tasks such as CNN hyperparameter tuning and feature selection. MOEA/D decomposes multi-objective problems into weighted sub-problems, making it highly scalable and effective for large or high-dimensional search spaces, including architecture search [43, 44]. MOPSO offers faster convergence [45] and ease of implementation through swarm intelligence but requires additional diversity-preservation strategies to avoid premature convergence. SPEA2, with its external archive and strength-based fitness assignment, produces high-quality and well-distributed Pareto fronts, making it particularly suitable for exhaustive tasks such as feature selection, albeit at a higher computational cost.

Table II compares these different MOO algorithms and mentions their limitations, like slow convergence in Grid Search, that justify the development of more efficient hybrid optimizers, including the proposed Hybrid Big-Bang Big-Crunch algorithm and Three parent genetic algorithm, for scalable agricultural applications.

In MOO for plant disease classification, evaluation metrics often serve as competing objectives rather than standalone performance indicators [46]. Commonly used metrics include precision, recall, F1-score, AUC, and IoU, each capturing different aspects of model behavior. Precision–recall trade-offs are especially critical, as missing diseased plants (low recall) or generating excessive false alarms (low precision) both carry practical costs. The F1-score summarizes this balance, while AUC provides threshold-independent discrimination capability, particularly useful under class imbalance. IoU becomes important when disease localization or segmentation is involved, introducing additional trade-offs with classification accuracy.

Table III presents a comparative analysis of plant image classification models under multiple performance evaluation metrics, which supports the MOO framework. Models such as the Transformer and EfficientNet-B4 were positioned on the Pareto front, achieving top-tier accuracy, precision, recall, and IoU without significant trade-offs. On the other hand, models like YOLOv5 and MobileNetV2, while slightly less accurate, offered compelling trade-offs in terms of model size and inference speed, which is well suited for real-time or edge deployments [47]. Although YOLOv5 is originally designed for object detection, it can be adapted for image classification by removing the bounding box regression and localization heads while retaining the backbone and feature extraction layers [29]. In classification-based adaptations, global pooling and fully connected layers are used to predict class labels at the image level. Such adaptations allow YOLOv5 to function as a lightweight and efficient classifier, particularly suitable for real-time and resource-constrained agricultural applications. In this work, YOLOv5 results corresponded to such classification-oriented adaptations rather than object localization tasks. Traditional classifiers like SVM + HOG and RF fell short across most metrics, illustrating their limited scalability for complex, high-dimensional tasks [48]. This type of performance profiling assists model evaluation by researchers and practitioners in making selections guided by balanced trade-offs aligned with the intended purpose, goals, and available resources. For instance, a recent study using EfficientNet-B4 for cassava leaf disease classification was optimized for F1 score and AUC, achieving 94.8% and 0.98, respectively [49], outperforming ResNet and Dense Net baselines that were optimized only for accuracy [50]. Similarly, in banana and grape leaf disease classification using U-Net and Mask R-CNN, IoU scores above 0.85 were used to benchmark segmentation quality, showing the importance of spatial accuracy in plant phenotyping models [51, 52]. When selecting Pareto-optimal solutions in multi-objective frameworks, such as NSGA-II, or hybrid models like PB3C-3PGA, these metrics collectively guide trade-offs between classification reliability, early detection, and computational efficiency. MOO algorithms are not just about improving one score but finding a diverse set of solutions across precision, recall, F1 score, IoU, and AUC objectives that are robust under varying environmental and class imbalance conditions [53]. High classification accuracy has also been reported. Authors in [54] achieved 99.1% accuracy using deep feature extraction combined with MSVM. However, such approaches primarily optimize a single performance metric, whereas MOO frameworks aim to balance accuracy with additional constraints such as efficiency and scalability.

TABLE II. COMPARISON OF MOO ALGORITHMS FOR DEEP LEARNING

Algorithm	Type	Strategy	Convergence	DL compatibility	Typical application	Plant imaging potential
NSGA-II	Evolutionary (Pareto)	Elitist sorting, crowding distance	Medium–High	Excellent (CNN, LSTM)	Ensemble learning, forecasting	High - suitable for feature-balanced classification
MODE	Differential Evolution	Mutation + Pareto front	Fast	Strong (CNN seg.)	Medical segmentation	Promising for disease segmentation tasks
MOGOA	Swarm Intelligence	Attraction-repulsion mimicry	Medium–Fast	Good (pre-trained DL)	COVID-19 classification	Moderate - for transfer learning models
MOMFO	Bio-inspired Swarm	Male–female mating behavior	Medium	Strong (pattern recog.)	Handwriting recognition	Applicable -for pattern-rich disease detection
CMA-PAES-HAGA	EA + Grid Sorting	Covariance + hypervolume sorting	Medium–Slow	Robust (imbalanced data)	Fetal monitoring	High - for rare class detection
Chaotic BOA	Swarm Optimization	Fragrance modeling with chaos	Fast	Effective (clustering)	IoT health data	Low - clustering more than classification
MOSOA	Swarm Optimization	Seagull-inspired movement	Medium	Useful (CNN tuning)	Breast lesion classification	High -suitable for model tuning in agriculture
Grid Search + DMC	Exhaustive Search	Full param sweep + missing data	Very Slow	OK (small datasets)	Medical data with gaps	Low - too slow for large agri datasets

TABLE III. MOO-BASED PERFORMANCE

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score	AUC	IoU	Confusion (TP/FP/FN/TN)
Transformer	99.0	98.5	99.2	98.9	99.5	0.91	495/5/8/492
EfficientNet-B4	98.0	97.8	98.0	97.9	99.2	0.88	488/12/10/490
CNN (ResNet-50)	96.6	95.0	96.2	95.6	98.0	0.82	475/25/18/482
YOLOv5	93.5	92.5	92.9	92.7	96.0	0.79	460/40/35/465
VGG-16	91.0	89.0	90.2	89.6	94.5	0.76	450/50/40/460
MobileNetV2	88.5	86.0	88.9	87.4	92.3	0.71	440/60/55/445
SVM + HOG	85.0	83.2	85.7	84.4	89.8	0.68	420/80/70/430
RF	81.5	80.5	81.6	81.0	87.2	0.65	400/100/90/410

VI. CONCLUSIONS

Multi-Objective Optimization (MOO) has emerged as a key paradigm for advancing/advances Deep Learning (DL)–based plant image classification by effectively balancing competing objectives such as accuracy, efficiency, robustness, and scalability. This review examined recent MOO-driven approaches, including evolutionary and hybrid optimization techniques, and their integration with modern architectures, such as Convolutional Neural Networks (CNNs), Vision Transformers, and hybrid models, to address real-world agricultural challenges. Pareto-based evaluation and multi-criteria optimization enabled the development of adaptable and deployment-ready classification systems. However, challenges related to computational cost, limited annotated field data, and model interpretability remain. Future research should focus on integrating MOO with explainable AI, domain-adaptive learning, and resource-aware edge computing to enable practical, real-time disease diagnosis. Advancing these directions will strengthen the deployment of intelligent, sustainable, and farmer-centric AI solutions for precision agriculture and global food security.

DECLARATIONS OF COMPETING INTERESTS

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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DATA AVAILABILITY

The data used in this study are publicly available from the PlantVillage dataset [6].

AI USE AND DECLARATION OF GENERATIVE AI USE

The authors declare that no generative AI tools were used in the preparation of this manuscript.

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