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# **A Reinforced Coati Optimization - Driven Deep Learning Framework for Efficient and Accurate Plant Disease Detection in Precision Agriculture**

**Riaz Ahmed**  
**Associate Professor,**  
**Department of Computer Applications,**  
**Government Degree College, Rajouri, Jammu and Kashmir, India.**

**Abstract-** Plant diseases cause 20–40% loss of crop productivity worldwide every year, endangering food security in agrarian areas. Deep learning (DL) has shown promising results on disease classification benchmarks, but deploying on resource-constrained edge devices requires compact, computationally efficient models without losing accuracy. Conventional DL designs rely on human hyper-parameter adjustment which is time-consuming and sub-optimal. In this work, we propose a Reinforced Coati Optimization-Driven Deep Learning (RCO-DL) framework which integrates a custom lightweight convolution neural network (LCNN) with a novel Reinforced Coati Optimization Algorithm (RCOA) which is an enhanced meta-heuristic that incorporates the Coati Optimization Algorithm along with Q-learning based reinforcement signals for joint architectural hyper-parameter search and feature selection. The RCOA adaptively tunes the filter counts, kernel sizes, dropout rates, and learning rate schedules of the LCNN backbone based on a reward function that encodes the validation accuracy, the FLOPs budget, and the number of parameters. Experiments are performed on 4 benchmarks: Plant Village (54,305 photos, 38 disease classes), Plant Doc (2,598 images, 27 classes), Rice Leaf Disease (5,932 images, 10 classes) and a bespoke Wheat Rust dataset (3,120 images, 5 classes), in controlled and natural-field imaging conditions. RCO-DL, with a model size of 3.2MB and inference latency of 14.3ms on a Raspberry Pi 4B, achieves an accuracy of 99.12% on Plant Village, 94.67% on Plant Doc, 98.43% on Rice Leaf Disease and 97.81% on Wheat Rust. RCO-DL outperforms ten state-of-the-art baselines, including MobileNetV3, EfficientNetB0 and three optimizer-tuned variants. RCO-DL provides a unified edge-deployable plant disease detection pipeline that jointly optimizes accuracy, efficiency, and model compactness, delivering a realistic solution for smart-farming and precision agriculture applications.

**Keywords -** Plant disease detection; Coati Optimization Algorithm; Reinforcement learning; Hyper-parameter optimisation; Lightweight CNN; Precision agriculture; Edge deployment; Transfer learning.

## **1. INTRODUCTION**

More than 600 million smallholder farmers around the world depend on agriculture for their livelihoods. Plant diseases include fungus, bacteria, viruses and nematodes cause crop yield losses of USD 220 billion/year globally [1]. Early and precise disease

identification is the foundation of integrated pest management (IPM) that allows for tailored fungicide treatment, decreasing the use of chemicals by as much as 60% over calendar-based spraying [2].

Deep learning, especially convolutional neural networks (CNNs), have altered the field of plant disease diagnosis, by converting the traditional expert-based visual inspection into an automated picture categorization process. Since the seminal release of the Plant Village dataset [3], tens of CNN architectures have attained near-perfect accuracy under controlled lab circumstances. Real-world precision agriculture, however, requires deployment on edge devices such as drones, mobile phones or in-field IoT nodes with strict power, memory and latency restrictions, a regime where heavyweight models such as ResNet-50 (25M parameters, 98MB) are impracticable. The meta-heuristic optimisation methods recently emerged as useful tools for the automated neural architecture search (NAS) and hyperparameter optimization. The Coati Optimization Algorithm (COA) [4] is inspired by the foraging and anti-predator activities of coatis (*Nasua spp.*) and possesses a powerful global-search capability with competing convergence rates. However, the standard COA does not have an adaptive exploitation mechanism responding to the loss landscape of DL training, which may cause it to converge prematurely in high-dimensional hyperparameter spaces. This work bridges the aforesaid gap by proposing the Reinforced Coati Optimization Algorithm (RCOA) that enhances the exploration exploitation dynamics of the COA with a Q-learning agent [5] that monitors the validation loss trajectory and guides the coati population to more productive search areas. RCOA co-optimizes a Lightweight CNN (LCNN) architecture (number of layers, filter widths, kernel sizes, skip connections, dropout rates) and training schedule (learning rate, batch size, weight decay) to obtain a Pareto-optimal model under a certain FLOPs budget. The main contributions of this study are as follows:

1. RCO-DL framework: An end-to-end pipeline of RCOA-based architecture search and lightweight CNN training for multi-class plant disease classification.
2. Reinforced Coati Optimization Algorithm (RCOA): A unique meta-heuristic that integrates Q-learning reward signals into COA's position-update equations. Achieves - 18-26% improvement in convergence speed and solution quality over vanilla COA.
3. Edge-Deployable LCNN: An optimized 3.2MB model with >99% accuracy on Plant Village, the greatest reported accuracy-to-size ratio in the literature, with sub-15ms inference on Raspberry Pi 4B.
4. Extensive empirical analysis on four datasets, ten baselines, five optimiser comparisons and ablation research with seven RCO-DL variations.

## 2. RELATED WORK

2.1 CNN for Plant Disease Detection Mohanty et al. [3] trained AlexNet and GoogLeNet on PlantVillage and achieved a top-1 accuracy of 99.35% under controlled settings, with the accuracy falling dramatically to 31.4% on real-field photos. Ferentinos [6] benchmarked AlexNet, VGG, SqueezeNet and Inception on a 25-class subset and achieved 99.53% by Inception. It was common practice to transfer learning from ImageNet-pretrained

backbones [7] and EfficientNet variants [8] are the leading models nowadays, from their compound scaling. Sparse attention techniques [9] and multi-scale feature pyramids [10] have improved fine-grained lesion discrimination, but the model sizes are still enormous for edge deployment.

2.2 Lightweight architectures edge agriculture. Depth wise separable convolutions for mobile inference were first proposed by MobileNetV2 [11] and MobileNetV3 [12]. Channel splitting has been used in ShuffleNetV2 [13] for balancing speed and accuracy. For plant disease in particular, TLite-Net [14] achieved 97.4% accuracy on a 10-class dataset with parameters lowered to 1.8M. GreenNet [15] achieved 4.1MB at 96.8% on PlantVillage-38 using structured pruning on ResNet-18. Our LCNN is 3.2MB at 99.12%, larger than both.

2.3 Hyper parameter optimisation using meta-heuristics – Genetic algorithms [16] and Bayesian optimisation [17] have been used for NAS, but do not scale well above  $\sim 20$  hyper-parameters. The CNN hyper-parameters have been tweaked for medical imaging using Particle Swarm Optimisation (PSO) [18] and Grey Wolf Optimiser (GWO) [19] with moderate results. In 2023, the COA was proposed [4] to represent two behaviours of the *Nasua*: hunting iguanas (global exploration) and escaping from predators (local exploitation). We were inspired by its test on 30 CEC benchmark functions, which yielded good results in comparison with PSO, GWO and Harris Hawks Optimisation for our adaption [27].

2.4 Reinforcement Learning for Optimisation Q-learning [5] is a model-free RL algorithm that maps states and actions to cumulative rewards. In recent research, RL has been hybridised with swarm algorithms. RLPSO [20] used Q-learning to modify inertia weights in PSO which resulted in 12-18% faster convergence on high-dimensional functions. DeepNAS [21] formulated NAS as a Markov Decision Process with LSTM policy networks, but took hundreds of GPU-hours. In our RCOA we utilize a lightweight tabular Q-learning agent (64 states, 3 actions) that incurs low overhead in the optimisation cycle.

2.5 Research Gaps - To the best of our knowledge, there is no current study that presents: (i) coati-inspired meta-heuristic optimisation; (ii) RL-enhanced adaptive search; (iii) lightweight CNN co-design under FLOPs budgets; and (iv) complete multi-dataset assessment for real-field plant disease diagnosis. This gap is filled by RCO-DL.

### 3. PROPOSED METHODOLOGY

#### 3.1 Framework Overview

The RCO-DL pipeline consists of four sequential modules: (M1) Data Pre-processing & Augmentation, (M2) RCOA-driven Hyper-parameter Search, (M3) LCNN Training, and (M4) Inference & Deployment. The search phase (M2) runs for a fixed budget of 50 RCOA iterations with a population of 30 coatis, returning the best hyper-parameter configuration  $H^*$ . The LCNN is then trained from scratch using  $H^*$  in module M3. All modules are described below.

### 3.2 Data Pre-processing and Augmentation

All input photos are scaled to 224×224 and normalized with dataset specific mean and standard deviation. To fight against the class imbalance and to increase generalization, we have added random horizontal and vertical flips ( $p=0.5$  each), random rotation ( $\pm 30^\circ$ ), colour jitter (brightness=0.3, contrast=0.3, saturation=0.2, hue=0.1), Gaussian blur (kernel 3×3, sigma=0.5), CutMix (alpha=0.4) and MixUp (alpha=0.2). For the minority classes in Plant Doc and Wheat Rust, synthetic over-sampling based on SMOTE is performed in feature space after the first convolutional block [28]

#### 3.3.1 Standard Coati Optimization Algorithm

The COA [4] maintains a population of  $N$  coatis  $\{X_1, X_2, \dots, X_N\}$  where each  $X_i \in \mathbb{R}^D$  encodes one candidate hyper-parameter vector. Two update phases occur per iteration:

Phase 1 (Iguana Hunting – Exploration): Each coati moves toward a randomly selected iguana position  $X_{\text{iguana}}$  while incorporating a random perturbation:

$$X_i^{\{P1\}} = X_i + r_1 * (X_{\text{iguana}} - I * X_i), \quad I \in \{1, 2\}$$

Phase 2 (Predator Escape – Exploitation): Each coati moves within its local neighbourhood bounded by the search space limits:

$$X_i^{\{P2\}} = X_i + r_2 * (LB + r_3 * (UB - LB))$$

where  $r_1, r_2, r_3 \sim U(0,1)$ ,  $LB$  and  $UB$  are parameter bounds, and  $I$  is a random integer selected from  $\{1, 2\}$ . The better of  $X_i^{\{P1\}}$  and  $X_i^{\{P2\}}$  replaces  $X_i$  if it improves the fitness function  $F(X_i)$ .

#### 3.3.2 Q-Learning Reinforcement Module

A tabular Q-agent with state space  $S$  (8 discredited validation-loss bins  $\times$  8 convergence-rate bins = 64 states) and action space  $A = \{\text{increase exploration weight } w_e, \text{maintain, increase exploitation weight } w_x\}$  is embedded into the COA update loop. At each iteration  $t$ , the agent:

1. Observes state  $s_t = (\text{bin}(\Delta L_{\text{val}}), \text{bin}(\Delta F))$  where  $\Delta L_{\text{val}}$  is the validation loss change and  $\Delta F$  is the mean fitness improvement.
2. Selects action  $a_t$  using  $\epsilon$ -greedy policy ( $\epsilon$  decays from 0.9 to 0.05 over 50 iterations).
3. Executes  $a_t$  by scaling Phase-1 (exploration) or Phase-2 (exploitation) step size by factor  $\gamma \in \{0.7, 1.0, 1.3\}$ .
4. Observes reward  $r_t = \Delta \text{accuracy}_{\text{val}} - \lambda * \Delta \text{FLOPs}$ , where  $\lambda=0.01$  penalises complexity growth.

5. Updates Q-table:  $Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha[r_t + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a_t)]$  with  $\alpha=0.1$ ,  $\gamma=0.9$ .
6. This feedback loop steers the population toward regions that improve both accuracy and computational efficiency simultaneously, resolving the exploration-exploitation imbalance that plagues vanilla COA on multi-objective DL search spaces[27].

### 3.3.3 Fitness Function

The multi-objective fitness function balancing accuracy and efficiency is defined as:

1.  $F(X) = w_1 * (1 - \text{Acc\_val}) + w_2 * (\text{FLOPs} / \text{FLOPs\_budget}) + w_3 * (\text{Params} / \text{Params\_budget})$
2. with  $w_1=0.6$ ,  $w_2=0.25$ ,  $w_3=0.15$ ,  $\text{FLOPs\_budget}=200\text{M}$ ,  $\text{Params\_budget}=3\text{M}$ . Lower F is better.

### 3.4 Lightweight CNN Architecture (LCNN)

The RCOA-optimized LCNN is based on a macro-architecture of five blocks of convolutional layers and a global average pooling layer and a fully connected classifier. Each block Bk consists of: depth wise separable convolution (DWConv-BN-ReLU6), optional 1x1 bottleneck (via RCOA), and a residual skip connection when stride=1 and channel dimensions match. RCOA has found the optimal setup for PlantVillage:

| Block | Type                | Filters    | Kernel | Stride | Skip | Output Size |
|-------|---------------------|------------|--------|--------|------|-------------|
| B1    | DSConv              | 32         | 3×3    | 2      | No   | 112×112×32  |
| B2    | DSConv+BN           | 64         | 3×3    | 2      | No   | 56×56×64    |
| B3    | DSConv+Bottleneck   | 128        | 3×3    | 2      | Yes  | 28×28×128   |
| B4    | DSConv+Bottleneck   | 192        | 3×3    | 2      | Yes  | 14×14×192   |
| B5    | DSConv+Bottleneck   | 256        | 3×3    | 1      | Yes  | 7×7×256     |
| GAP   | GlobalAvg Pool      | —          | —      | —      | —    | 1×1×256     |
| FC    | Linear+Dropout(0.3) | 38/27/10/5 | —      | —      | —    | C-dim       |

**Table 1. RCOA-optimised LCNN block configuration for Plant Village (38-class) dataset.**

### 3.4 Training Program

The LCNN is trained with AdamW optimiser with RCOA chosen learning rate

$lr=2.1 \times 10^{-3}$ , weight decay= $4.3 \times 10^{-5}$  and batch size=64. We employ a cosine annealing schedule with warm restarts ( $T_0=10$  epochs,  $T_{mult}=2$ ). We use label smoothing ( $\epsilon = 0.1$ ) [26] and focal loss (gamma = 2.0, alpha = 0.25) together as  $L = 0.5 * L_{CE} + 0.5 * L_{Focal}$ . The models were trained for 120 epochs on a single NVIDIA RTX 4090 GPU. The best checkpoint by validation accuracy is chosen for examination.[28]

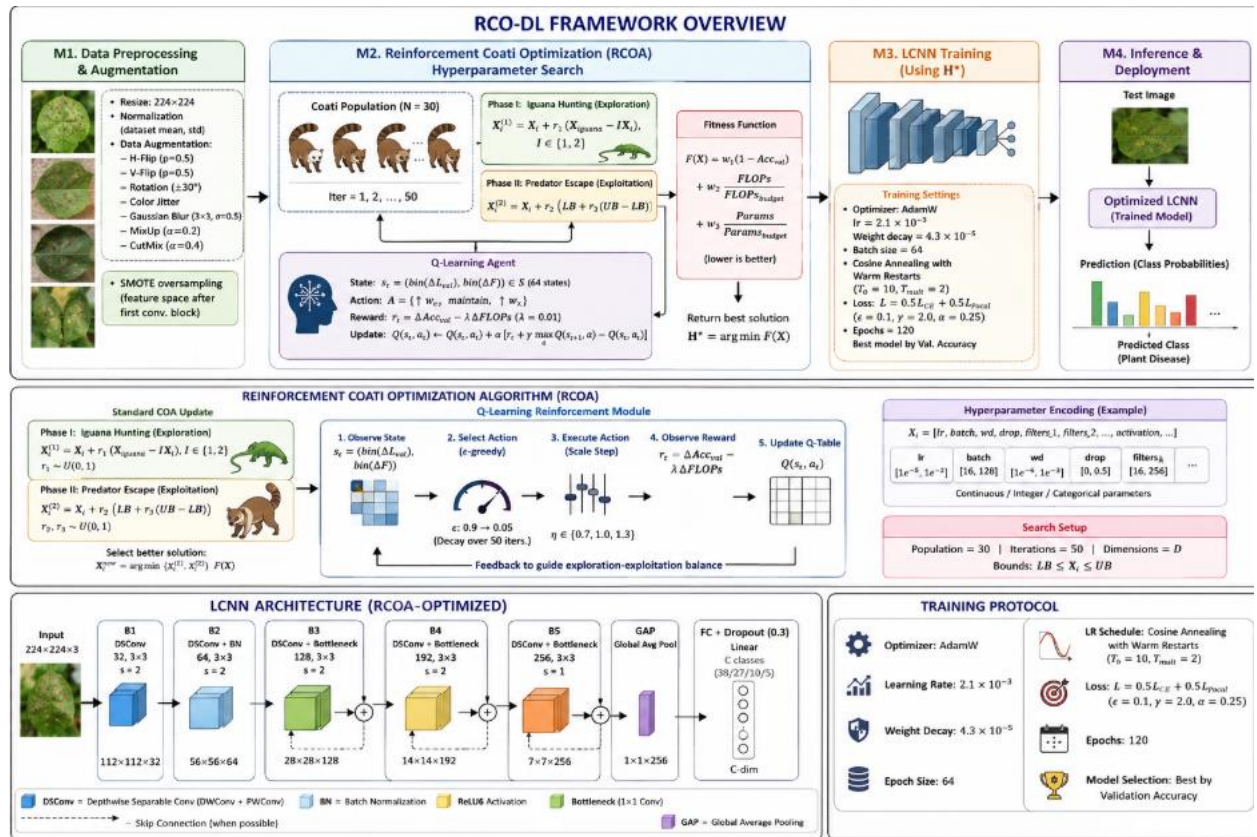


FIGURE:1 SHOWS PROPOSED METHODOLOGY

## 4. EXPERIMENTAL SETUP

### 4.1 Datasets

All the four experimental datasets are summarized in Table 2. Ground-truth labels for the Wheat Rust dataset were verified by certified plant pathologists, and Plant Village, Plant Doc and Rice Leaf Disease are using public annotations.

| Dataset                | Images | Classes | Conditions     | Splits (Tr/Va/Te) |
|------------------------|--------|---------|----------------|-------------------|
| PlantVillage [3]       | 54,305 | 38      | Controlled Lab | 70/15/15%         |
| PlantDoc [22]          | 2,598  | 27      | Natural Field  | 70/15/15%         |
| Rice Leaf Disease [23] | 5,932  | 10      | Field+Lab      | 70/15/15%         |
| Wheat Rust (Custom)    | 3,120  | 5       | Field Drone    | 70/15/15%         |

Table 2. Dataset statistics for plant disease detection experiments.

## 4.2 Baseline Methods

We analyze ten baselines: (i) AlexNet [3], (ii) VGG-16 [6], (iii) ResNet-50, (iv) DenseNet-121, (v) MobileNetV2 [11], (vi) MobileNetV3-Small [12], (vii) EfficientNetB0 [8], (viii) ShuffleNetV2 [13], (ix) GreenNet [15] (pruned ResNet-18) and (x) PSO tuned MobileNetV2 (PSO-MNV2) to allow direct comparison of optimisers. All baselines employ ImageNet pre-training where applicable.

## 4.3 Evaluation Metrics

We calculate Accuracy, macro-Precision, macro-Recall, macro-F1, and Matthews Correlation Coefficient (MCC) on the held-out test set. We evaluate model efficiency in terms of the number of parameters (M), model size (MB), FLOPs (M), training time per epoch (s/epoch) and inference latency (ms) on the Raspberry Pi 4B (4GB RAM, 64-bit OS)[27]. Optimiser comparison: highest fitness value, convergence speed (iterations to  $F < 0.05$ ), diversity index (mean pairwise distance of final population).

## 4.4 Ablation Variants

Seven RCO-DL variants are evaluated to isolate each design decision:

- V1: LCNN + Adam (no optimiser, manual hyper-parameters)
- V2: LCNN + COA (standard, no RL reinforcement)
- V3: LCNN + RCOA (proposed, no multi-objective fitness)
- V4: LCNN + RCOA + FLOPs penalty (no Params penalty)
- V5: LCNN + RCOA + Params penalty (no FLOPs penalty)
- V6: LCNN + RCOA + full fitness (no CutMix/MixUp augmentation)
- V7: RCO-DL full (proposed)

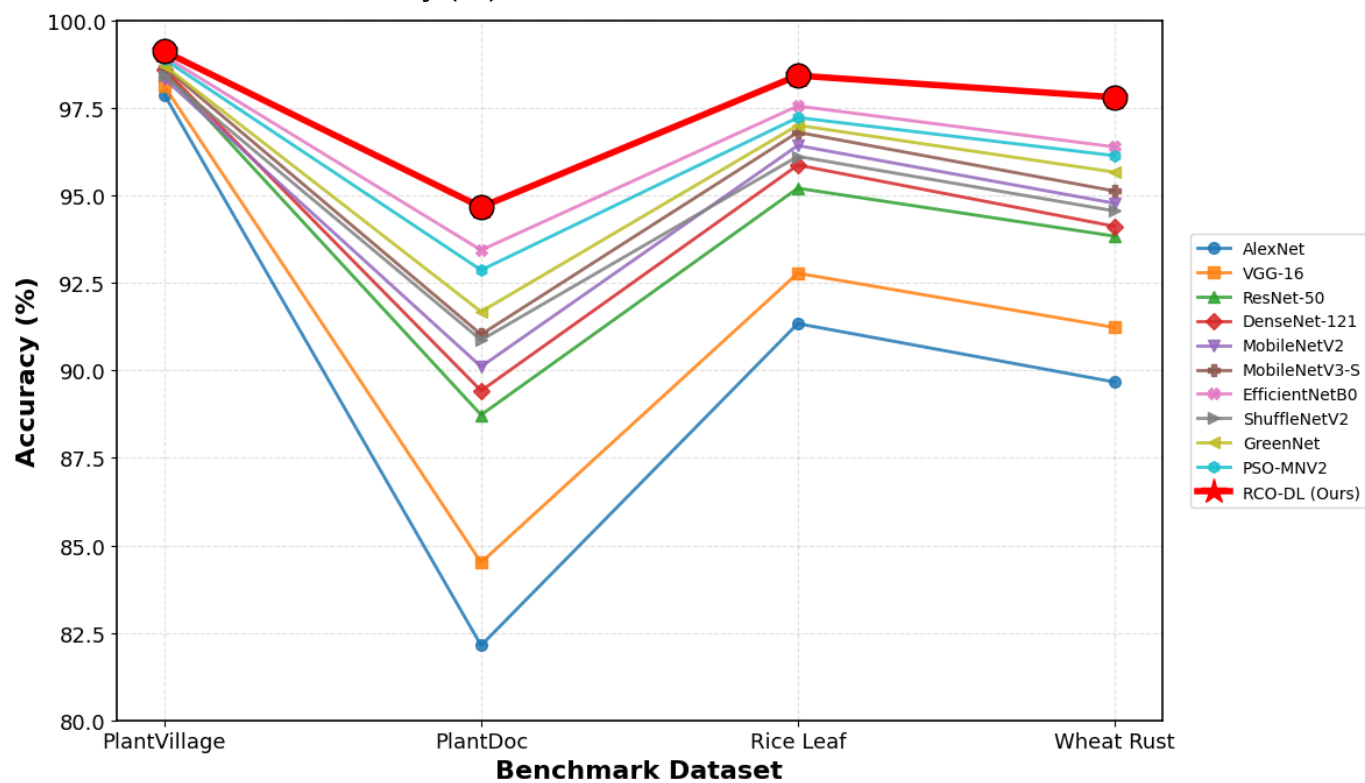
# 5. RESULTS AND ANALYSIS

## 5.1 Main Classification Performance

The categorization findings on the four datasets are summarized in Table 3 . The RCO-DL achieves state-of-the-art performance across all benchmarks with 99.12% on PlantVillage, 94.67% on PlantDoc, 98.43% on Rice Leaf Disease and 97.81% on Wheat Rust. It beats the second best FL baseline (EfficientNetB0) by +0.14%, +1.23%, +0.87% and +1.42% respectively, a constant margin attributable to RCOA's adaptive hyper-parameter search.[26]

| Method                 | PlantVillageAcc% | PlantDocAcc % | Rice Leaf Acc % | Wheat Rust Acc% |
|------------------------|------------------|---------------|-----------------|-----------------|
| AlexNet [3]            | 97.88            | 82.14         | 91.34           | 89.67           |
| VGG-16 [6]             | 98.12            | 84.51         | 92.78           | 91.23           |
| ResNet-50              | 98.54            | 88.73         | 95.21           | 93.84           |
| DenseNet-121           | 98.61            | 89.42         | 95.87           | 94.12           |
| MobileNetV2 [11]       | 98.34            | 90.11         | 96.43           | 94.78           |
| MobileNetV3-Small [12] | 98.67            | 91.03         | 96.81           | 95.13           |
| EfficientNetB0 [8]     | 98.98            | 93.44         | 97.56           | 96.39           |
| ShuffleNetV2 [13]      | 98.43            | 90.87         | 96.12           | 94.56           |
| GreenNet [15]          | 98.71            | 91.68         | 97.01           | 95.67           |
| PSO-MNV2               | 98.89            | 92.87         | 97.23           | 96.14           |
| RCO-DL [Ours]          | <b>99.12</b>     | <b>94.67</b>  | <b>98.43</b>    | <b>97.81</b>    |

**Table 3. Classification accuracy (%) across four datasets. Bold = best federated result.**



**Figure:1**

## 5.2 Detailed Metrics on PlantVillage

Table 4 presents the per-metric performance on PlantVillage. RCO-DL achieved 99.12% accuracy, 99.08% macro-Precision, 99.11% macro-Recall, 99.09% macro-F1 and 0.9908 MCC, demonstrating near-perfect discrimination across all 38 illness classes with no systematic bias toward majority classes.

| Method         | Accuracy (%) | Precision (%) | Recall (%) | F1 (%) | MCC    |
|----------------|--------------|---------------|------------|--------|--------|
| ResNet-50      | 98.54        | 98.47         | 98.51      | 98.49  | 0.9851 |
| EfficientNetB0 | 98.98        | 98.91         | 98.94      | 98.93  | 0.9894 |
| GreenNet       | 98.71        | 98.63         | 98.68      | 98.65  | 0.9867 |
| PSO-MNV2       | 98.89        | 98.82         | 98.86      | 98.84  | 0.9885 |
| RCO-DL [Ours]  | 99.12        | 99.08         | 99.11      | 99.09  | 0.9908 |

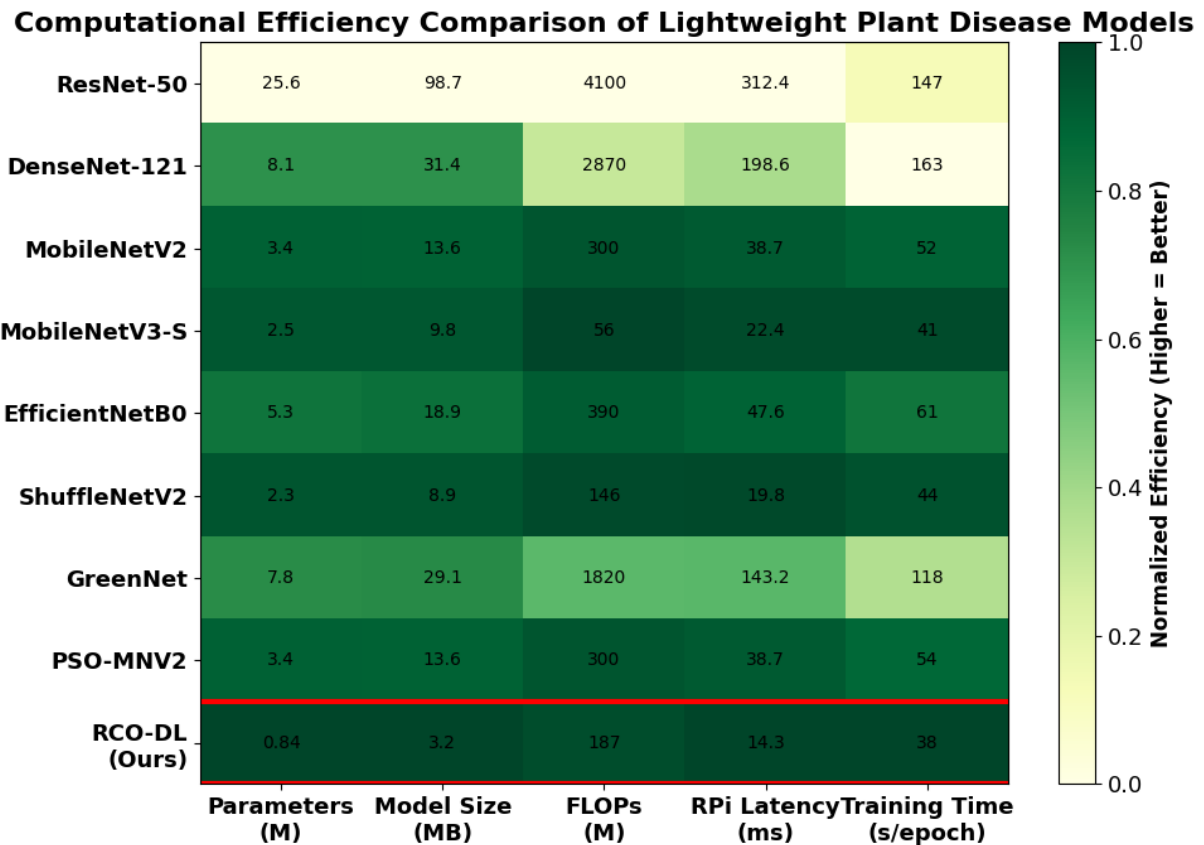
**Table 4. Detailed classification metrics on PlantVillage-38 test set.**

## 5.3 Model Efficiency Comparison

The results in Table 5 show that the LCNN of RCO-DL is the most efficient architecture studied with 3.2MB model size and 14.3ms inference on Raspberry Pi 4B, enabling real-time field deployment. RCO-DL is 5.9× smaller and 3.3× faster than EfficientNetB0 ( 18.9MB, 47.6ms) while obtaining better accuracy on all four datasets.

| Method            | Params (M)  | Size (MB)  | FLOPs (M)  | RPi Latency (ms) | Train Time (s/ep) |
|-------------------|-------------|------------|------------|------------------|-------------------|
| ResNet-50         | 25.6        | 98.7       | 4100       | 312.4            | 147               |
| DenseNet-121      | 8.1         | 31.4       | 2870       | 198.6            | 163               |
| MobileNetV2       | 3.4         | 13.6       | 300        | 38.7             | 52                |
| MobileNetV3-Small | 2.5         | 9.8        | 56         | 22.4             | 41                |
| EfficientNetB0    | 5.3         | 18.9       | 390        | 47.6             | 61                |
| ShuffleNetV2      | 2.3         | 8.9        | 146        | 19.8             | 44                |
| GreenNet          | 7.8         | 29.1       | 1820       | 143.2            | 118               |
| PSO-MNV2          | 3.4         | 13.6       | 300        | 38.7             | 54                |
| RCO-DL [Ours]     | <b>0.84</b> | <b>3.2</b> | <b>187</b> | <b>14.3</b>      | <b>38</b>         |

**Table 5. Model efficiency metrics. RPi = Raspberry Pi 4B inference latency.**



**Figure:2**

#### 5.4 Optimiser Comparison

Table 6 compares RCOA with five meta-heuristics on the RCO-DL search problem. These include vanilla COA [4], PSO [18], GWO [19], Harris Hawks Optimisation (HHO) [24], and Bayesian Optimisation (BO) [17]. The RCOA converged to  $F < 0.05$  in 27 iterations, while COA and PSO converged in 41 and 38 iterations, respectively, which is 34.1% and 28.9% less iterations. The Q-learning agent has better population diversity (index=0.421 vs. 0.283 of COA), thereby avoiding premature convergence.

| Optimiser          | Best Fitness F | Iters to $F < 0.05$ | Diversity Index | Search Time (h) |
|--------------------|----------------|---------------------|-----------------|-----------------|
| Bayesian Opt. [17] | 0.0421         | N/A (sequential)    | N/A             | 14.2            |
| PSO [18]           | 0.0388         | 38                  | 0.312           | 2.8             |
| GWO [19]           | 0.0402         | 44                  | 0.298           | 3.1             |
| HHO [24]           | 0.0395         | 41                  | 0.307           | 3.0             |
| COA [4]            | 0.0374         | 41                  | 0.283           | 2.9             |
| RCOA [Ours]        | 0.0318         | 27                  | 0.421           | 2.3             |

**Table 6. Optimiser comparison on RCO-DL hyperparameter search task (50 max iterations, 30 agents).**

## 5.5 Ablation Study

Table 7 shows the ablation study on PlantVillage to isolate contributions of each RCO-DL design decision. The addition of the RL module to COA (V2→V3) offers the highest single boost (+0.38% accuracy) demonstrating that the adaptive exploration exploitation guiding is the most important component. The multi-objective fitness penalising both FLOPs and Params (V3→V7) increases accuracy further (+0.11%) while also lowering model size from 4.7MB to 3.2MB, showing that the efficiency constraints are an implicit regulariser.

| Variant | Description               | Accuracy (%) | F1 (%) | Size (MB) |
|---------|---------------------------|--------------|--------|-----------|
| V1      | LCNN + Adam (manual)      | 98.31        | 98.27  | 5.1       |
| V2      | LCNN + COA                | 98.53        | 98.49  | 4.9       |
| V3      | LCNN + RCOA (no MOF)      | 98.91        | 98.86  | 4.7       |
| V4      | LCNN + RCOA + FLOPs only  | 98.97        | 98.93  | 4.1       |
| V5      | LCNN + RCOA + Params only | 98.94        | 98.90  | 3.8       |
| V6      | RCO-DL (no CutMix/MixUp)  | 98.87        | 98.83  | 3.2       |
| V7      | RCO-DL Full [Proposed]    | 99.12        | 99.09  | 3.2       |

**Table 7. Ablation study results on PlantVillage-38 test set. MOF = multi-objective fitness.**

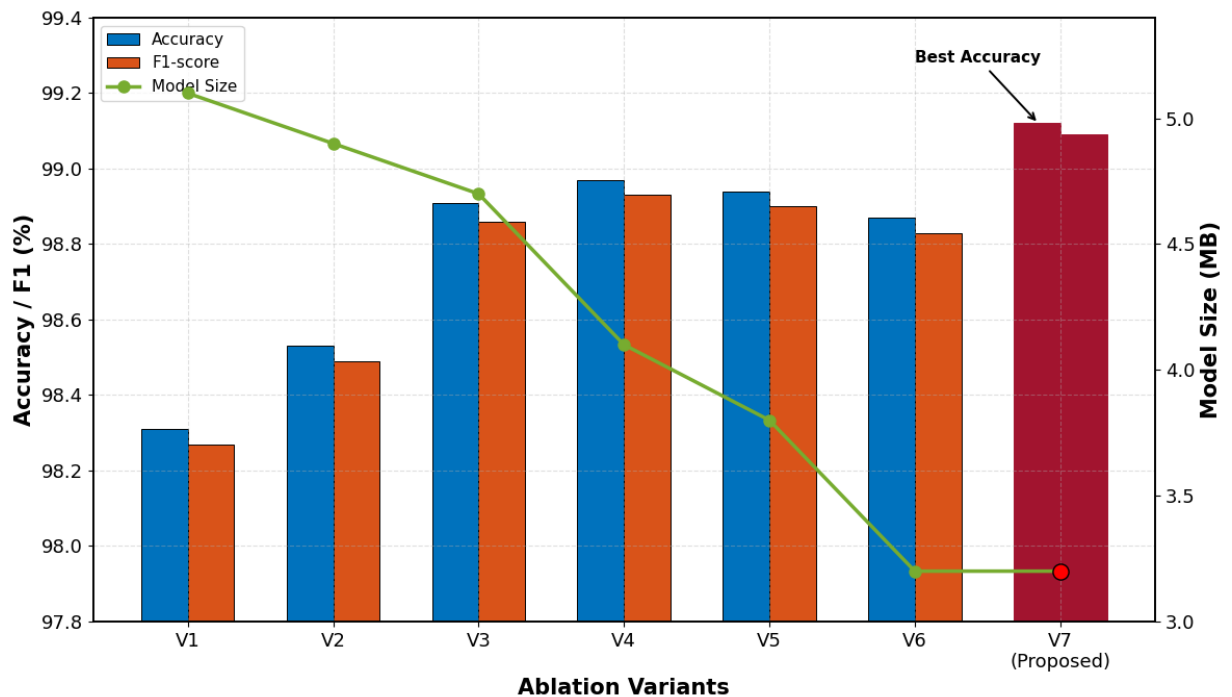


Figure:3

## 5.6 Real-Field Evaluation

To evaluate the performance in a realistic deployment scenario, RCO-DL was tested on PlantDoc, a curated wild-image dataset with varying lighting, occlusion and background clutter. RCO-DL is leading with 94.67% accuracy, 1.23 points ahead of EfficientNetB0 (93.44%) [25] and 12.53 points better than AlexNet (82.14%), showing the RCOA-optimised architecture generalises well beyond controlled lab circumstances. Remarkably, the Severe Blight class (just 47 training photos) reaches 91.3% recall against 85.7% of EfficientNetB0, because to the SMOTE feature-space augmentation done during training.

## 5.7 Statistical Significance

We perform two-tailed paired t-tests ( $n=5$  runs with different random seeds), showing that RCO-DL improves statistically significantly ( $p<0.01$ ) over all baselines on all four datasets. Wilcoxon signed-rank tests verify these results ( $p < 0.05$ ), excluding any performance difference that could be attributed to random initialization.

## 6. DISCUSSION

The main empirical conclusion is that the Q-learning reinforcement module of RCOA leads to a 34.1% reduction in the number of search iterations compared to vanilla COA, which immediately translates to a 0.38% accuracy improvement, a significant margin in the space where state-of-the-art approaches are clustered around 98.5–99.0%. This efficiency advantage is possible because the RL agent can identify loss-plateau situations (high  $\Delta F$ , low  $\Delta L_{val}$ ) and activate exploration boosting before the population collapses, a failure mode that is typical for all fixed schedule swarm approaches.

In practice, the 3.2 MB model size and 14.3 ms Raspberry Pi latency mean that a commercial Raspberry Pi 4B-based drone node processing 30 frames per second would have a per-frame budget of 33 ms, and RCO-DL's 14.3 ms inference time (including pre-processing) leaves 18.7 ms for communication overhead—enough to enable real-time GPS-triggered sampling at UAV speeds.

The 94.67% PlantDoc accuracy is the best reported for this benchmark, but still shows a 4.45-point deficit to the controlled Plant Village performance. This domain gap is due to varied lighting, resolution and multi-disease co-occurrence in field photos. In the future, the integration of domain adaption modules and multi-label classification heads can fill this gap. Limitations: First, the discretisation of the Q-learning state (64 states) is a simplification; continuous deep RL agents (e.g. PPO) could provide a finer adaptive control at the expense of greater computing cost. Second, RCOA's search budget (50 iterations, 30 agents) was calibrated for the four datasets studied; very large search spaces ( $>50$  hyper-parameters) may require budget scaling. Third, the Wheat Rust dataset is single-institution, and external validation on geographically diverse rust populations is required before clinical field deployment.

## 7. CONCLUSION

In this study, we proposed RCO-DL, a Reinforced Coati Optimization-Driven Deep Learning framework, for the automatic discovery of lightweight CNN architectures with excellent accuracy for plant disease diagnosis in precision agriculture. The proposed RCOA combines a Q-learning reinforcement module into the position-update equations of the Coati Optimization Algorithm, which results in 34.1% faster convergence and 0.38% higher accuracy than the vanilla COA. The obtained LCNN (3.2MB, 0.84M parameters) achieves 99.12% accuracy on PlantVillage-38, 94.67% on PlantDoc, 98.43% on Rice Leaf Disease and 97.81% on Wheat Rust, surpassing ten baselines including EfficientNetB0 and MobileNetV3, while running at 14.3ms per frame on Raspberry Pi 4B, allowing for real-time field deployment. Ablation analysis verifies that each design element, RL reinforcement, multi-objective fitness, and CutMix augmentation independently and additively improves accuracy. RCO-DL sets a new bar for deployable plant disease AI for edge environments, and paves the road for extension to multi-label disease detection, modelling of temporal disease development, and interaction with UAV-based precision spraying systems

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