ISSN: 2182-2069 / E-ISSN: 2182-2077

Innovative Mechanism for Smart Agriculture with Identification of UAV-Aided Spray Areas

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Received: September 09, 2025; Revised: October 17, 2025; Accepted: December 10, 2025; Published: February 27, 2026

Abstract

Smart agriculture uses technology to enhance farming processes, with Unmanned Aerial Vehicles (UAVs) as a crucial tool for aerial imaging, crop monitoring and precision spraying. The inability of existing research to precisely identify spray regions impedes the effective control of pests and diseases in agricultural settings. In this study, we present the development of the Clonal Flower Pollination integrated Adaptive radial deep neural network (CFPO-ARDNN), which uses data from UAV s to identify spray zones. The classifier was evaluated in agricultural settings using an RGB camera, considering five distinct croplands. To assess and test the created system, high-resolution UAV photos were employed in five distinct target fields: pea, apricot, strawberry, peach and coriander. The Joint Photographic Experts Group (JPEG) converter, RGB to hue saturation intensity (HSI), Wavelet Transform and Local Binary Pattern (LBP) for feature extraction were all used in the preparation of the video. In comparison, the CFPO-ARDNN model outperformed the others in predicting the following: strawberry (91.85%), Apricot (96.56%), Peach (95.67%), Coriander (93.47%) and pea (94.45%). The experiment's findings demonstrate how well the suggested CFPO-ARDNN model works in comparison to the current approaches.

Keywords: Unmanned Aerial Vehicles (UAVs), Smart Agriculture, Local Binary Patterns, Clonal Flower Pollination Integrated Adaptive Radial Deep Neural Network (CFPOARDNN).

Journal of Interner Services and Information Security (JISIS), volume: 16, number: 1 (February-2026), pp. 111-126. DOI: *10.58346/JISIS.2026.I1.007*

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1 Introduction

UAVs also known as drones, are flights that have remote control capability or built-in computer programs without a human pilot (Singh & Nair, 2022). Historically, UAVs have been primarily used for military purposes, where they were positioned in dangerous regions to launch armed attacks and conduct remote surveillance to reduce pilot deaths. Nowadays, a variety of sectors employ UAVs, such as package delivery, telecommunication, precision agriculture, traffic management, aerial inspection, photography, as well as search and rescue operations (Ali et al., 2024). The UAV is a cutting-edge tool that has been effectively applied in commercial, military and public domains. According to Business Intelligence (BI), there will be more than 29 million UAVs in use in the future. UAVs with cameras and sensors perform various sensing activities like autonomous target recognition, precision agriculture, water stress measurement and air quality index monitoring. A high uplink rate is required for the UAV communication network to send sensory data for further processing (Gargalakos, 2024). UAV technology, which includes Wi-Fi radio interfaces, sensors, embedded microcomputers, batteries and GPS, is easily accessible and inexpensive, which has led to its broad application in both military and civilian sectors. As a result, it has the potential to be a part of future wireless communication systems (Arafat et al., 2020). Rotorcraft and fixed-wing versions are the two types of UAVs. While rotorcraft UAVs may perform vertical take-off and landing (VTOL) by employing their rotor wings to create thrust force for mobility, fixed-wing UAVs are more aerodynamically efficient because of their relative velocity (Zuo et al., 2022). UAVs can be used in conjunction with wireless communication networks to quickly extend wireless connectivity to mobile devices beyond terrestrial infrastructure. UAVs can serve as mobile aerial base stations for emergency communication services in conflict zones, disaster areas, high-traffic areas, blind spots and rural regions, offering two key advantages. First, a UAV's mobility and agility features allow it to fly quickly, getting close to people and responding quickly to surges in demand for its services. Second, because line-of-sight (LOS) links provide more dependable communication channels, UAVs operating at high altitudes can connect to ground users more reliably than traditional terrestrial base stations (Meng et al., 2023). UAVs can be used for a broad range of functions, enabling the creation of various helpful applications like phone calls and Internet access, also improving the measurement of ground end-user satisfaction, or quality of experience (QoE) (Alzahrani et al., 2020). UAVs are utilized for various purposes, including industrial inspection, emergency medical assistance, border patrol, surveillance, reconnaissance, remote sensing, target acquisition, infrastructure monitoring, communications support and aerial imaging (Dixit & Subramaniam, 2025). They detect, perceive processes, communicate, plan and make decisions using actuators and control algorithms (Bauk et al., 2020). Smart agriculture is a modern technique that optimizes resource use and increases agricultural production by utilizing crop and land management (Alipour et al., 2016). It focuses on addressing location and time parameters in crop cultivation to reduce environmental impact and enhance agricultural productivity (Al-Turjman & Altiparmak, 2020). The main advantages of utilizing UAVs for smart agricultural applications are their adaptability to changing weather patterns and their capacity to take high-definition images at a variety of distances (with an average range of 50 to 100 metres). UAVs can also be employed to evaluate and monitor crop quality and to keep monitoring animal, weed and pest threats (Maddikunta et al., 2021). The objective of the study is to identify the UAV-aided spray areas in smart agriculture with suitable deep-learning methods (Maksumkhanova et al., 2025). To identify the UAV-aided spray areas, we proposed a Clonal Flower Pollination integrated Adaptive radial deep neural network (CFPO-ARDNN).

Using electronic equipment and sub-systems, such as web applications, UAVs, local controllers, weather sensors and multispectral cameras, Gagliardi et al., (2021) created a precision farming architecture to track the health of the vines. Two prototype sites were built to evaluate the design's performance in real-world conditions. Ukaegbu et al., (2021) created a precision farming architecture that made use of electronic devices and sub-systems to monitor vine health. Despite a scant assessment of scalability and environmental effect, two pilot sites were established, exhibiting successful weed detection and pesticide spraying (Maaroof & Bouhlel, 2025). Drones in smart farming enhance conventional methods, lessen environmental issues and attain sustainable agriculture were employed and Drones were equipped with advanced sensors to monitor crop health, weed control and irrigation scheduling, while also assessing soil quality and monitoring crop health (Pungavi & Praveenkumar, 2024). Embedded technology, IoT and UAVs were used to construct a mobile agricultural monitoring system (Anna et al., 2025). To reduce needless water irrigation, the system made use of water pumps, Arduino microcontroller boards, environmental sensors and Wi-Fi modules to measure temperature, soil moisture and humidity (Karar et al., 2021, Popescu et al., 2020). A hierarchical approach for precision agricultural crop monitoring, combining UAVs with WSNs (Kovalev et al., 2023), which enhances agricultural performance and precision, as demonstrated in a Romanian study.

Through the digitalization of UAV transport and technical cycles examined by (Prabhu et al., 2021), the use of UAVs in smart farming emphasizes the potential for effective data and analytical aid in flow control systems and logistics monitoring decision-making processes. A few of the variables that affect UAV spray quality include droplet diameter and dispersion. To provide an affordable and safe alternative to weed control using visible light and near-infrared technologies on a UAV (Ajayi et al., 2023). The system included an accurate sprayer and a lithium-ion battery-powered weed identification system. The UAVs protect farmers and customers from odours and negative impacts.

Motivation

The motivation for using UAVs in smart agriculture is well-grounded, given their capability to ensure performance, reduce exertion prices, and reduce environmental effect compared to traditional spraying strategies. UAVs can exactly target spray areas, reduce chemical use and ensure even distribution, that is important for sustainable farming. The integration of the Clonal Flower Pollination Optimized Adaptive Radial Deep Neural Network (CFPO-ARDNN), in addition, refines this method via correctly identifying optimal spray zones, leveraging UAV-collected data to enhance decision-making and overall crop control.

The following structure provides the foundation for the paper's organization. Methodologies are shown in section 2. Section 3 presents the results of the simulation. We conclude the article and discuss prospects in section 4.

2 Methods

The experimental strategy of the study is described in the methodology, which includes processes like datasets, preprocessing, optimization and classification. The overall methodology’s structure is represented in Figure 1.

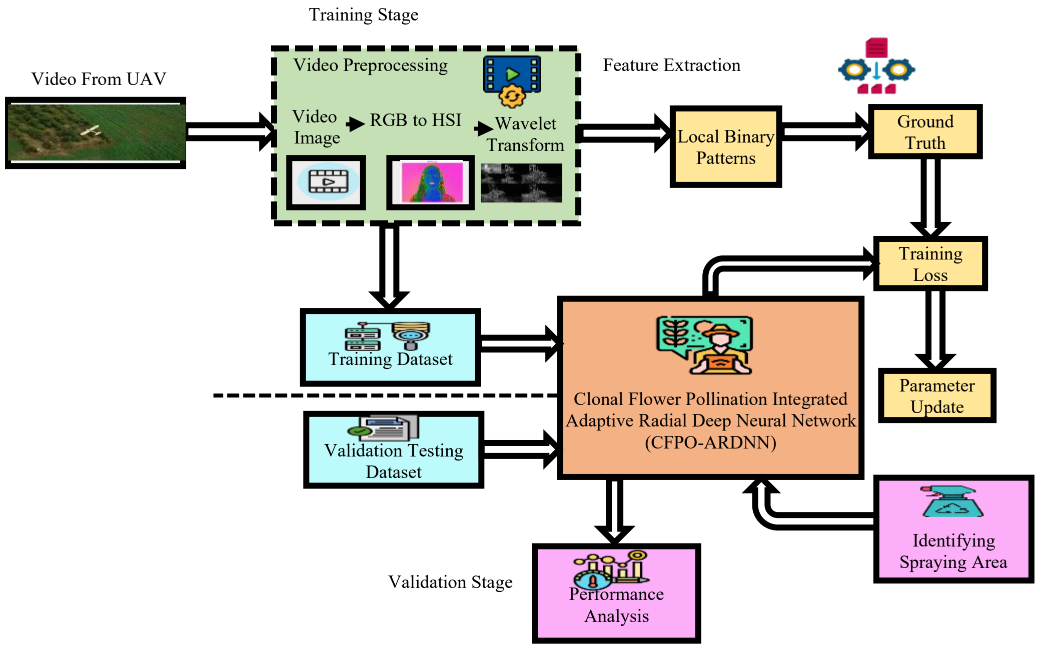

Figure 1: Overview of methodology

Dataset Acquisition

The UAV drone is used in a dataset to capture detailed images, accounting for changes in sunlight intensity. The UAV drone have high-resolution RGB camera aids in identifying and classifying infected crops. Although not equipped with a multispectral sensor, it captures different light wavelengths for plant health analysis. The thermal sensor integrated with UAV, can detect temperature variations in crops, indicating plant stress or disease. It features autonomous flight modes enhancing data collection efficiency. The UAV also supports GPS-based navigation for precise control and stability during image acquisition.

Video Preprocessing

Video preprocessing involves several procedures to enhance data quality and usefulness. The JPEG converter converts video into images, RGB to Hue-Saturation-Intensity transformation performs color correction and noise reduction techniques like Wavelet Transform reduce artifacts. These steps increase data eligibility for analysis and use in intelligent agricultural systems, making it more suitable for intelligent agricultural systems.

Video to Image Conversion using JPEG Converter

The videos were gathered by UAV s and converted to JPEG format using a JPEG converter. Two classifier datasets, one comprising crops (strawberry, apricot, peach, coriander, and pea), were gathered for the system of crop identification. For every field, there were 2700 and 2900 labelled images of crops.

Color Correction using RGB to HSI

Video processing often uses color correction from RGB to HSI (Hue, Saturation and Intensity) to enhance the appearance and color balance of photographs. RGB represents colors based on their intensities, but it’s not always visible to the human eye. The HSI model divides color data into hue, saturation and intensity components, aligning with human perception.

The following Equation (1) has been used to convert RGB to HSI colour space.

$$H = \begin{cases} \theta, & if B \leq G \\ 360 - \theta, & if B > 0 \end{cases} \tag{1}$$

$$\text{with} \theta = \cos^{-1}\left\{\left(\frac{\frac{1}{2}[(R-G)+(R-B)]}{[(R-G)^2+(R-B)(G-B)]^{1/2}}\right)\right. \tag{2}$$

The Saturation component can be found using Equation (3).

$$S = \left[1 - \frac{3}{R+G+B}\right][(\min(R+G+B)] \tag{3}$$

"The Intensity/Value component" can be computed by the following Equation (4).

$$I = \frac{1}{3}(R+G+B) \tag{4}$$

It is expected that RGB values have been normalized among 0 and 1 for the conversions described above and that the angle theta is calculated about the HSI colour space's red axis. By dividing each value by 360 degrees from Equation (1), the hue value can be normalized to $[0, 1]$. RGB values that have been normalized to $[0, 1]$, will already include the other two components.

Noise Reduction Using Wavelet Transform

Wavelet transform-based wavelet denoising techniques remove noise in signals by zeroing coefficients with a value below the threshold. The term "soft threshold" refers to reducing coefficients that remain after the threshold value is applied. This technique produces the best denoising with minimal signal distortion when the threshold value is used appropriately. This study outlines three phases of the threshold-based wavelet denoising technique.

The number of breakdown layers, wavelet filter choice and discrete wavelet transform:

$$Y(e) = Y(h) + Y(a) \tag{5}$$

For noisy data, the high-frequency wavelet transform coefficient is represented by $Y(e)$, $Y(h)$, $Y(a)$ in Equation (5) data that is both true and noisy.

Select a threshold for each wavelet and level the high-frequency coefficient. By using the threshold, the transform coefficient $\hat{Y}(h)$ was calculated. It utilized both soft and hard thresholds, for example, in Equations (6) and (7). For them, T is the threshold.

$$\hat{Y}(h) = \begin{cases} sgnY(e)Y(e-T), & |Y(e)| \geq \mathrm{T} \\ 0 & , \; |Y(e)| < T \end{cases} \tag{6}$$

$$\hat{Y}(h) = \begin{cases} Y(e), |Y(e)| \geq \mathrm{T} \\ 0 \quad , |Y(e)| < T \end{cases} \tag{7}$$

$\hat{Y}(h)$ wavelet reconstruction to estimate $\hat{g}(u)$ is given by Equation (8)

$$\hat{g}(u) = \omega^{-1}\hat{Y}(h) \tag{8}$$

The wavelet inverse transform operator in Equation (8) is represented by ω^{-1}. The wavelet transform filter method uses threshold schemes like Minimaxi, Sqtwolog, Heursure and Rigrsure. Under non-ideal situations, Minimaxi selects the mean square extreme error, Heursure mixes the first two, and Sqtwolog uses a preset threshold of $\sqrt{2 \times \log(length(z))}$ and Rigrsure uses the Stein unbiased likelihood principle to establish an adaptive threshold. Threshold modification methods affect the denoising effect, with the first method based on the global threshold and the second on the hierarchical threshold for each level of noise.

Feature Extraction Using Local Binary Pattern (LBP)

The study encodes rotation-invariant uniform local texture patterns using a rotation-invariant uniform LBP employing image windows that represent sub-images of plant pixels. In a single bit-wise transition $(0\ to\ 1\ or\ 1\ to\ 0)$, this conveys features. It is vulnerable to rotational changes, nevertheless, which are unsuitable for places with native plants. More encoding from rotation-invariant uniform LBP to micro-features is required to get around this restriction.

$$\mathrm{LBP}_{\mathrm{Q,R}}^{\mathrm{riu2}} = \begin{cases} \sum_{\mathrm{q=0}}^{\mathrm{Q-1}} \mathrm{t}\left(\mathrm{h_q} - \mathrm{h_d}\right), & \text{if } \mathrm{V}\left(\mathrm{LBR_{Q,R}}\right) \leq 2 \\ \mathrm{Q}+1, & \text{otherwise} \end{cases} \tag{9}$$

$P$is the number of neighbours and R represents the radius from the centre, with the center being represented by subscript c and the current pixel by subscript p.

$$t(x) = \begin{cases} 1: & w \geq 0 \\ 0, & w < 0 \end{cases} \tag{10}$$

$$\mathrm{V}\left(\mathrm{LBR_{Q,R}}\right) = \left|\mathrm{t}\left(\mathrm{h_{q-1}} - \mathrm{h_d}\right) - \mathrm{t}(\mathrm{h_0} - \mathrm{h_d})\right| + \sum_{\mathrm{q}}^{\mathrm{Q-1}} \left|\mathrm{t}\left(\mathrm{h_q} - \mathrm{h_d}\right) - \mathrm{t}\left(\mathrm{h_{q-1}} - \mathrm{h_d}\right)\right| \tag{11}$$

Equation (10) represents pixel differences, with s as a threshold and $\mathrm{h_d}$and $\mathrm{h_q}$representing center and neighbor pixels. Equation (11) calculates U, indicating spatial transitions and a uniform pattern. A $P\ +\ 2$ feature with uniform patterns $U \leq\ 2$ is the resultant of $LBP_{Q,R}^{riu2}$.

Identification of UAV-Aided Spray Areas Using Clonal Flower Pollination Optimization Integrated Adaptive Radial Deep Neural Network (CFPO-ARDNN)

An Adaptive Radial Deep Neural Network (ARDNN) is linked to the Clonal Flower Pollination Optimization (CFPO) in smart agriculture to optimize UAV-assisted spray zones. To increase spray area identification and targeting accuracy and efficacy, CFPO-ARDNN employs sophisticated optimization techniques and deep learning algorithms. Through innovative thinking, crop protection in agricultural contexts can be enhanced while utilizing fewer resources.

Adaptive Radial Deep Neural Network (ARDNN)

The ARDNN offers numerous benefits in UAV-aided spray area identification. Its radial basis feature layers enhance the model's ability to capture complicated, nonlinear relationships in data, enhancing accuracy in distinguishing goal regions. This adaptability enhances effective identity of most beneficial spray zones, contributing to efficient and unique agricultural applications.

To manage the intelligent irrigation system and minimize sensor mistakes, three layers of processing come together. The layers of adaptive radial deep neural networks can be of several kinds such as Input Layer (i), Hidden Layer (ii) and Output Layer (iii). Each of these three tiers' neural network application layers is made up of a different set of components and characteristics. The required water is then pushed using pumping motors after preliminary calculations and predictions are performed in the designated period. The initial configuration of all the parameters is zero. The input layers are where data is transmitted and collected from the sensor unit at the first step. Data is gathered from agricultural regions using Hidden Layers and sent for additional data processing. The processing unit receives a constant stream of information on the Output Layer parameters. The entire data are calculated using Pearson correlations. Algorithm 1 represents the pseudo-code for ARDNN.

Algorithm 1: ARDNN

Step 1: $Input value obtained from the sensor$

Step 2: *To add* $0\ to\ 1,$ *read all sensor data. Usually, the multidimensional* (A_j) *soft-max function is used.*

$$SOFTMAX(A)_j = \frac{exp(A_j)}{\sum_i exp(A_j)}$$

Step 3: *The irrigation system's data set* $\mathrm{E}(\mathrm{y},\mathrm{z})$ *sensor node, and this control unit cooperates because the logarithmic function keeps the gradient of* $\log(\rho\theta\left(\frac{z}{y}\right))$ *from having very small values.*

Step 4: *The hard threshold function, water duration sequence, and soil moisture level experimental data were used to conduct the training method.*

$$C(y) = max(0, z)$$

Step 5: *For every training batch, the total data points* x, y*'s error has to be determined.*

$$\varepsilon_j = \frac{\sum_{j=1}^{n} \omega_n^u * J(X_n \neq i_u(y_n))}{\sum_{j=1}^{n} \omega_n^{(u)}}$$

Subsets are identified, and the similarity between two or more is calculated using the sum of the digital values.

Clonal Flower Pollination Optimization (CFPO)

CFPO offers numerous advantages for UAV-aided spray area identification. It efficiently explores and exploits the search area by combining global and local search techniques, leading to optimal solutions with high accuracy. CFPO's clonal selection and flower pollination operators enhance convergence speed and solution quality.

Clonal Flower Pollination Optimization (CFPO) is a complicated method inspired by process dynamics. The two categories under which it falls are biotic pollination, which happens when pollinators like insects carry pollen across great distances and global pollination, which is also referred as Levy features. CFPO can be cumbersome and hasten the point of convergence; however, it works well for solving optimization problems. For these problems, several adjustments have been proposed as solutions, such as altering the parameter values or fusing CFPO with other algorithms. The study found that using the multilayer thresholding enhanced the performance of an augmented CFPO.

Probability of Adaptive Switching: The performance of the CFPO is significantly influenced by the switching probability (Q), which affects both local and global pollination. To ensure efficient exploitation and exploration processes, an adaptive switch probability is presented to steer the algorithm towards a fast and effective convergence. The following Equation (12) is the general equation for the probability of an adaptive switch:

$$\mathrm{Q} = \mathrm{Q_{min}} + (\mathrm{Q_{max}} - \mathrm{Q_{min}}) \times \left(0.5 \times \left(1 - \frac{\mathrm{u}}{\mathrm{u_{max}}}\right) + 0.5 \times \frac{\mathrm{f_{max,u}} - \mathrm{f_{aver,u}}}{\mathrm{f_{max,u}} - \mathrm{f_{min,u}}}\right) \tag{12}$$

Where $\mathrm{Q_{max}}$ and $\mathrm{Q_{min}}$ are set by the user at first. The maximum, minimum and average iteration values at iteration u are represented by the values $\mathrm{f_{max,u}}$, $\mathrm{f_{aver,u}}$, and $\mathrm{f_{min,u}}$, respectively. The current generation is denoted by u. Switch probability is influenced by repetitions and individual fitness values. It starts at the start of iteration when population evolution is efficient, and as a parameter u approaches $\mathrm{u_{max}}$, it is mostly influenced by fitness values, increasing algorithm dependability in local and global search.

Modified Local Pollination: A modified self-pollination approach is put forth, incorporating both a polynomial and a Cauchy distribution. The algorithm can make significant sense of the modified strategy, which enhances the program's ability to prevent premature convergence and escape from the local optimum. The modified method for self-pollination is provided by Equation (13).

$$z_j^u = hbest + G(y_j^u - y_k^u) + G(y_n^u - y_o^u) \quad (13)$$

Where hbest is the current best solution; G from a Cauchy distribution and y_j^u, y_k^u, y_n^u, and y_o^u represent pollen gathered from various flowers of the same plant species at each iteration u.

Switching and Selection Methods: The initial CFPO requires local or global pollination to achieve optimal results. To address communication issues and premature aging, crossover and selection processes are used to increase population variety, with a user-defined crossover rate (CR) between0 and 1.

$$s_j^u = \begin{cases} z_j^u, & \text{if rand CR} \\ y_j^u, & x \geq 0 \end{cases} \quad (14)$$

Here z_j^u is a newly created person following a global and local search, and y_j^u is the target individual. A selection procedure is conducted to determine the survival of an individual, either the trial or the target, into the next generation. In the following generation, the trial person will take the position of its target individual if it produces a higher value of the objective function at iteration $u = u + 1$The matching formula is as follows:

$$y_j^{u+1} = \begin{cases} s_j^u, & \text{if } f(s_j^u) \geq f(y_j^u) \\ y_j^u, & \text{otherwise} \end{cases} \quad (15)$$

The function to be maximized is denoted by f $(.)$An enhanced algorithm called the CFPO is suggested in this section. Algorithm 2 demonstrates the pseudocode for CFPO-ARDNN.

Algorithm 2: CFPO-ARDNN

```
Step 1: Initialize Parameters
Initialize UAV_data
Initialize Population of Flower Individuals
Initialize Radial Deep Neural Network (R − DNN) Parameters
Set Number of Generations
Set Mutation Rate
Set Crossover Rate
Step 2: Define Fitness Function
def fitness_function(individual)
  # Use UAV_data and R − DNN to evaluate fitness
  fitness = evaluate_R − DNN(individual, UAV_data)
  return fitness
Step 3: Clonal Flower Pollination Optimization
for generation in range(Number_of_Generations):
     for individual in Population
      individual.fitness = fitness_function(individual)
    Population.sort(key = lambda x: x.fitness, reverse = True)
     Clones = select_top_individuals(Population)
    for clone in Clones
     if random() < Crossover_Rate
            offspring = crossover(clone, random.choice(Population))
       Population.append(offspring)
```

$if\ random() < Mutation\_Rate$
$mutate(clone)$
$for\ individual\ in\ Population$
$individual.fitness = fitness\_function(individual)$
$Population = select\_best\_individuals(Population)$
$\boldsymbol{Step\ 4}: Training\ Adaptive\ Radial\ Deep\ Neural\ Network$
$best_{individual} = Population[0]$
$train\_R - DNN(best\_individual, UAV\_data)$
$\boldsymbol{Step\ 5}: Use\ Trained\ R - DNN\ for\ UAV - aided\ Spray\ Area\ Identification$
$spray\_areas = identify\_spray\_areas(best\_individual, UAV\_data)$
$return\ spray\_areas.$

3 Results and Discussion

For training, research uses the Google Tensorflow-Keras module, which is freely available, together with Python 3.8 on Anaconda. The laptop's powerful 11th Gen Intel Core i7-1165G7 CPU, clocked at 2.80GHz, with Intel Iris Xe technology, provides improved graphics. It can easily multitask with its enormous 512 GB of disc capacity and 16 GB of RAM. Researchers have used the existing methods, which include "Recurrent Convolutional Neural Network (R-CNN) (Khan et al., 2021), YOLO-V3 (Redmon, 2018)" for the identification of UAV-aided spray areas.

Figure 2 displays the model testing results over a 100-epoch period. Figure 2 (a) displays the accuracy of the proposed model after testing and training. From there, research can reasonably estimate that our model can protect data in about seventy epochs. This illustrates how the suggested paradigm accommodates variations in sunlight intensity. Figure 2 (b) illustrates the training and testing loss of the recommended method. The figure illustrates our minimal loss, implying that the recommended strategy would result in the fewest errors under optimal sunlight conditions.

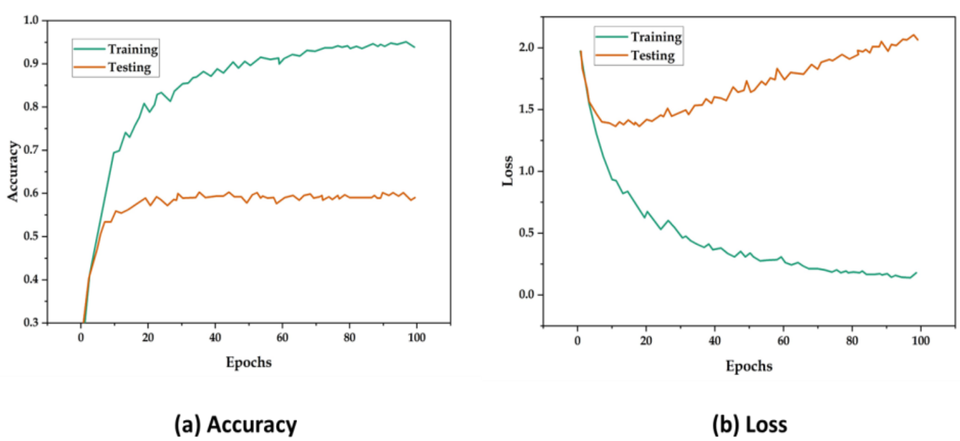

Figure 2: Accuracy and loss graph

Accuracy: Accuracy is a generally used metric to estimate the performance of classification models, and it is also applied for image segmentation for the identification of UAV-aided spray areas. Out of all the examples in the dataset, it shows the number of accurately predicted situations. Table 1 depicts the accuracy analysis of the classifier identification system. Table 2 and Figure 3 depict the comparison of accuracy for existing and proposed methodologies. Figure 3 shows the accuracy on training and validation.

Table 1: Accuracy analysis of the classifier identification system

Location (croplands)	Work pattern	Cropland	
	Classifier	**Spray**	**Non-Spray**
Pea	Spray	356	40
	Non-Spray	48	349
	Accuracy (%)	**94.92**	
Strawberry	Spray	275	32
	Non-Spray	47	230
	Accuracy (%)	**93.38**	
Apricot	Spray	287	27
	Non-Spray	39	260
	Accuracy (%)	**95.78**	
Peach	Spray	275	36
	Non-Spray	41	270
	Accuracy (%)	**93.88**	
Coriander	Spray	285	42
	Non-Spray	47	280
	Accuracy (%)	**92.55**	

Table 2: Outcome of accuracy

Methods	Accuracy (%)				
	Pea	**Strawberry**	**Apricot**	**Peach**	**Coriander**
RCNN (Khan et al., 2021)	90.85	89.36	91.35	89.92	89..22
YOLO V3 (Redmon, 2018)	89.23	85.31	87.91	86.13	87.84
CFPO-ARDNN [Proposed]	94.45	91.85	96.56	95.67	93.47

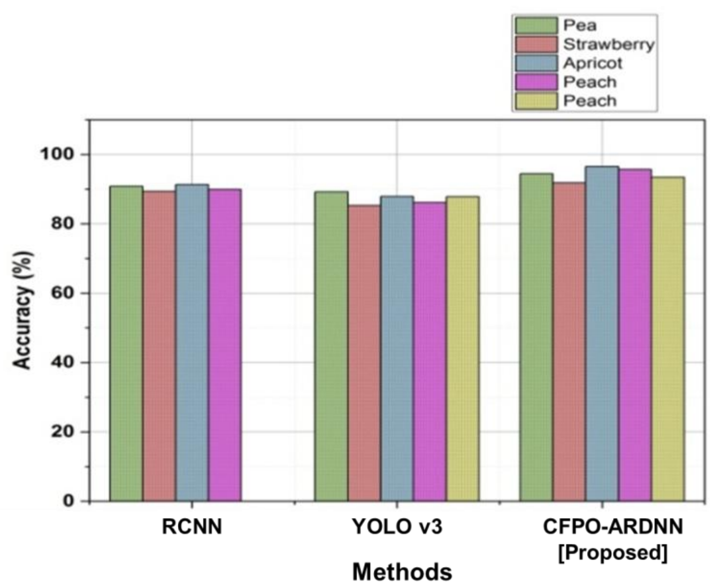

Figure 3: Accuracy comparison between existing and proposed techniques

Precision: The difference between the total number of positives predicted by the model and the number of True Positives (TP) is computed. Precision based on the 1000 epochs is shown in Figure 5. Figure 4 illustrates the accuracy rate achieved by the proposed methodology. Compared to other methods, the suggested model achieves an accuracy rate of 96.73%. In comparison, naive Bayes, KNN, and RF had accuracy rates of 94.23%, 95.85%, and 93.45%, respectively. DAFA-XGBoost has superior outcomes compared to other existing methods.

Recall: Recall, also known as sensitivity, measures how accurate the positive predictions were in comparison to the actual data. The Recall based on the 1000 epochs is shown in Figure 6.

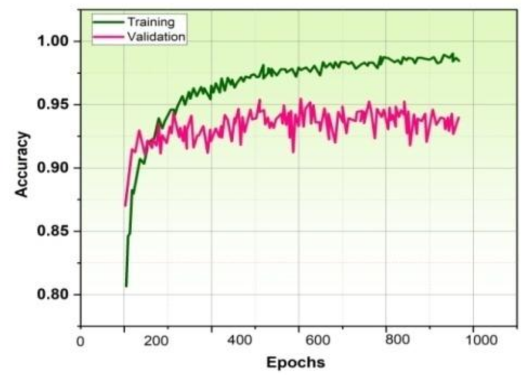

Figure 4: Accuracy based on the 1000 epochs on training and validation

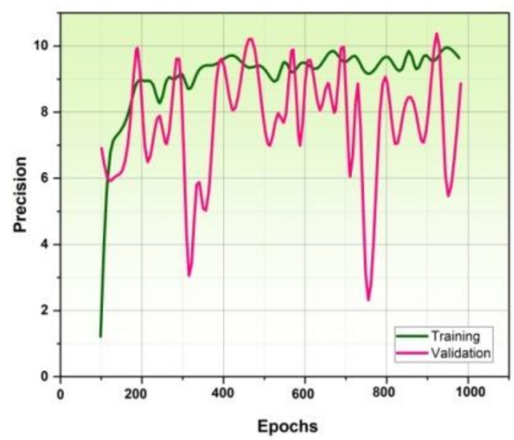

Figure 5: Precision based on the 1000 epochs on training and validation

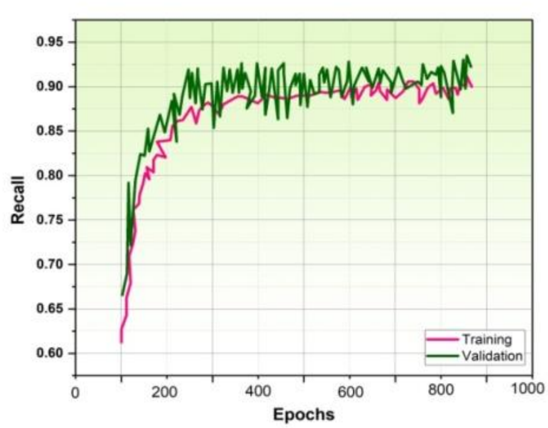

Figure 6: Recall based on the 1000 epochs of training and validation

F1-Score: The F1-Score is broadly used as a statistic to calculate the performance of classification algorithms, including those used to identify faults. The F1-score based on the 1000 epochs is shown in Figure 7.

The purpose of conducting field trials in various fields was to enhance the range of datasets available for selecting spray and non-spray zones within croplands. The classifiers could only be trained and tested on datasets obtained in the late autumn; they were only applied to croplands. Encouraging outcomes were noted after thorough experimentation. To increase the recognition accuracy of the ARDNN, a variety of experimental field datasets were included for testing and training. The model's learning process reduces training loss in later epochs, indicating better performance as loss decreases.

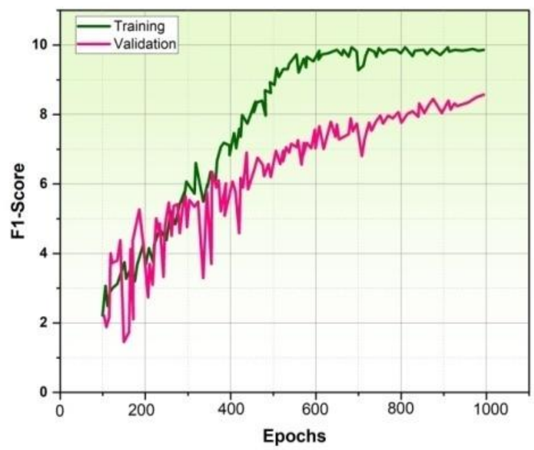

Figure 7: F1-score based on the 1000 epochs on training and validation

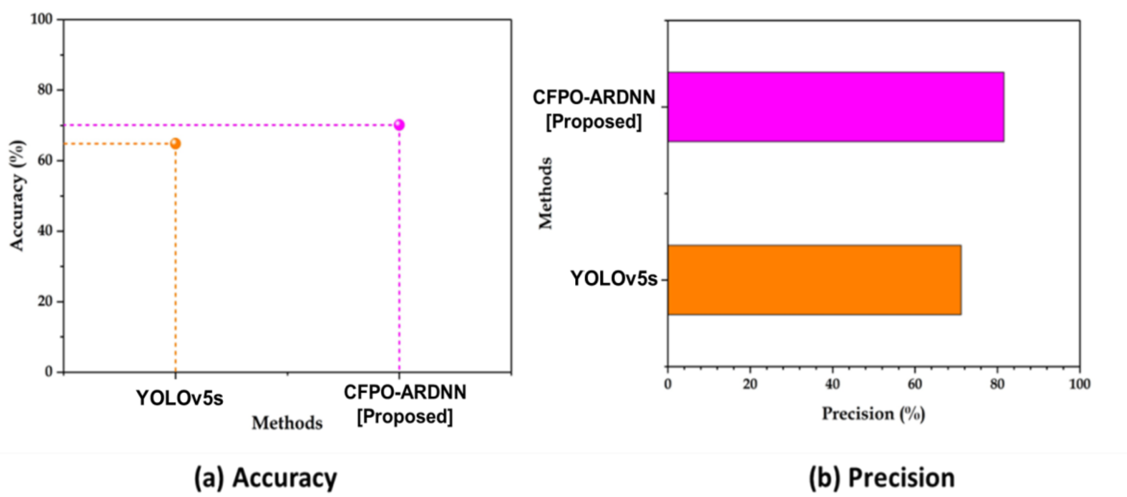

Figure 8: Results of accuracy and precision

Figure 8 illustrates the accuracy and precision achieved by the suggested approach. In contrast to other methods, the suggested model accomplishes an accuracy of 70.1% and a precision rate of 81.6%. In comparison with the YOLOv5 accuracy rate of 64.8% and precision rate of 71.2% respectively. CFPO-ARDNN has superior outcomes compared to other existing methods for identifying spray zones.

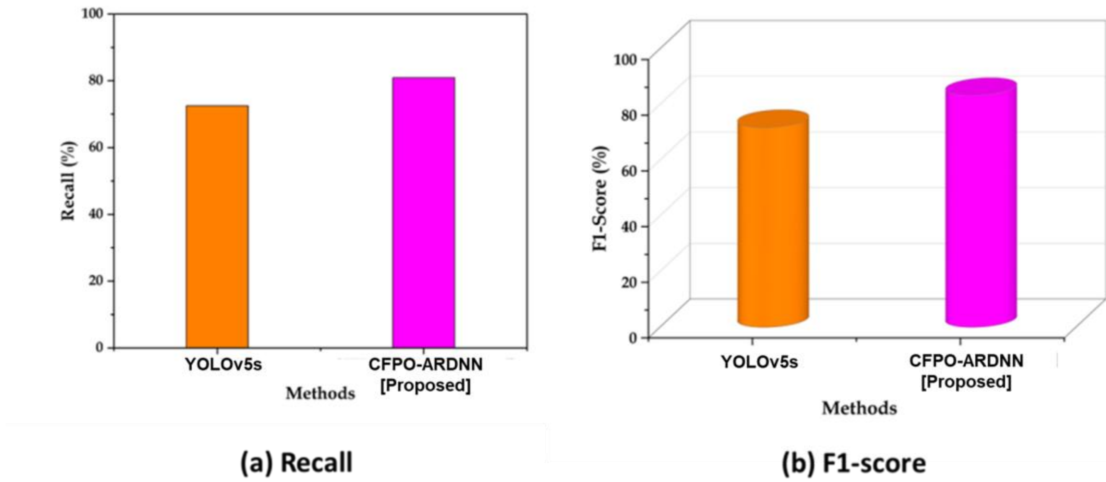

Figure 9: Results of recall and F1-score

Figure 9 shows the recall and F1-score accomplished by the suggested approach. In contrast to other methods, the suggested model achieves a recall and F1-score of 80.9%, 83.3%. In comparison with YOLOv5s had recall and F1-score rates of 72.5%, 71.8%. When compared to other existing methods, CFPO-ARDNN produced better results for identifying spray zones. Table 3 shows the values of suggested and existing methods.

Table 3: Outcome of Suggested and Existing Methods

Method	Method	Precision (%)	Recall (%)	F1-score (%)
YOLOv5s (Ajayi et al., 2023)	64.8%	71.2%	72.5%	71.8%
CFPO-ARDNN [proposed]	70.1%	81.6%	80.9%	83.3%

RCNN struggles with slow inference instances because of its multi-stage processing, which impacts real-time programs. YOLO V3, whilst faster, may struggle with small object detection and lacks precision in complex scenes due to its constant anchor containers. YOLOv5s, even though improved in speed and accuracy, can still face challenges with high-density object detection and varying object scales. The CFPO-ARDNN overcomes those limitations by leveraging UAV facts to ensure spatial resolution and context understanding. CFPO-ARDNN utilizes an ARDNN mixed with clonal flower pollination optimization to tune detection accuracy and robustness in dynamic environments. This integration allows for extra specific identification of spray zones, addressing issues associated with small item detection, density, and real-time overall performance.

4 Conclusion

In this study, we present the development of the Clonal Flower Pollination integrated Adaptive radial deep neural network (CFPO-ARDNN), which uses data from UAVs to identify spray zones. The CFPO-ARDNN optimizes pesticide and herbicide efficacy while reducing chemical use by utilizing UAV data and video preprocessing techniques like Wavelet Transform, JPEG conversion, RGB to HSI conversion, and LBP for the extraction of features. The CFPO-ARDNN model outperforms other techniques in terms of accuracy for strawberry (91.85%), Apricot (96.56%), Peach (95.67%), Coriander (93.47%) and pea (94.45%) indicating its potential for efficient pest and disease management along with sustainable farming methods, highlighting deep learning as well as unmanned aerial vehicle technology. The CFPO-ARDNN technique, a UAV method for crop health assessment, faces challenges due to environmental factors like wind and temperature. An RGB camera may not capture all necessary spectral records, and data processing demands can create bottlenecks. High costs and regulatory compliance issues also pose challenges. Future development could improve the technique by integrating advanced sensors, refining algorithms, and using hybrid optimization techniques. This would provide detailed data for crop health assessments and precise spray zone identification. Technological advancements could lower costs, make high-performance systems more accessible, and streamline compliance and deployment. Lastly, improving UAV resilience to environmental factors and creating adaptive algorithms could enhance performance and accuracy across different agricultural settings.

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